

Spatial Access to Healthcare: Exploring the Provision of Local Services

Daniel James Lewis

**Department of Geography
University College London (UCL)**

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Author's Declaration

I, Daniel James Lewis, confirm that the work presented in this thesis "*Spatial Access to Healthcare: Exploring the Provision of Local Services*" is exclusively my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis. This work was undertaken with the partial support of the Economic and Social Research Council (ESRC) and Southwark Primary Care Trust (PCT). The views expressed in this publication are those of the author alone and not necessarily of the ESRC, Southwark PCT, or University College London (UCL).

Signed,

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Abstract

This thesis creates a context for exploring the provision of local healthcare services quantitatively, with particular focus on the application of spatial analysis and the use of geographic information systems (GIS). It focuses theoretically on the intersections between: health and medical geography; GIScience and spatially integrated social science; and social justice and spatial equity, elucidating the value of space and place in understanding patient registration with, and usage of, healthcare services.

The practical elements of the thesis are based on patient registration data provided by Southwark primary care trust (PCT), and Hospital Episode Statistics from the NHS Information Centre. Focussing initially on primary care, registration with GP surgeries in Southwark is considered firstly from a normative perspective, and subsequently by employing a service area delineation approach. Profiling GP surgeries in this way enables an insight into patient registration behaviours, and sheds light on the challenges of implementing an agenda of patient choice as advocated by recent NHS white papers. The perspective of inpatient and outpatient care is also considered, given the increasing import of joined up provision in primary and secondary care. The thesis considers the linkage between the two service hierarchies, investigating utilisation of secondary care by patients.

The value of this thesis derives from its relevance to the reform agenda that looks likely to radically reshape the NHS, the exploitation of patient registration data at individual level, novel use of classification, and the systematic application of spatial analysis across a range of scales.

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I look forward to further research, and new opportunities.

Up against the Ivory Tower

I'm sitting here (at a cafe) thinking
about writing a poem. What will I write
about? I don't know. I just feel like it
when suddenly a young man in a hurry
walks up to me and says, "Can I use your
pen?"

There's an envelope in his hand. "I want
to address this." He takes my pen
and addresses the envelope. He's very serious
about it. He's really using the
pen.

Richard Brautigan, 1970.

From a collection of poetry entitled "Rommel Drives on Deep into Egypt", published by
Delacorte Press/Seymour Lawrence, New York.

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1. Introduction

1.1 The enduring importance of geography in healthcare analysis

This is a thesis about geography, about spatial thinking, and about developing an understanding of the characteristics of local provision of healthcare services. Against a backdrop of sweeping changes to the welfare geography of the UK, both in terms of the operation of the National Health Service (NHS), and more broadly in the expression of a British society, the enduring significance of space is indisputable.

There are numerous aspects that are important to understanding the relevance of geography to health and healthcare research, and more often than not their significance lies not solely within a single discipline, but across many. The core of this research derives from the sub-disciplines of geographic information science (GIScience), and health and medical geography. Additionally, the importance of public health policy, epidemiology, ecology and other social policy aspects cannot be underestimated.

Whilst a discussion of the literature particularly pertinent to each chapter is conducted on a chapter by chapter basis, it is important to set a general context for this thesis. To this end, this introduction discusses several key areas of academic insight to the work: health and medical geography; GIScience and spatially integrated social science; health and healthcare equity; access to healthcare; and a brief outline of the NHS. Subsequent to this, the aims and objectives of the thesis are discussed, as well as the funding and ethical context, before the structure of the thesis is expanded upon.

1.1.1 Health and Medical Geography

Without wishing to rehash extensive, historic, on-going, and at times divisive, debates about “what is” health and/or medical geography, it is nonetheless necessary to sketch out their relevance to the thinking behind this thesis. It is particularly important because the work was conceived under this banner, and derives insight and understanding as a result of a broader disciplinary background in geography, as opposed to an adjacent health-related field; this thesis is, therefore, primarily the work of a geographer.

The basis for health and medical geography stems from the belief that “our ‘health’ and our ‘geographies’ are inextricably linked” (Gatrell and Elliott, 2009 p.3). Whilst there are numerous ways of seeing the world that privilege the role of space and place in understanding health, a distinction is often made between two arbitrary camps – the health geographers, and the medical geographers. Kearns and Collins (2010) contend that health geography emerged from medical geography, retaining key foci such as empirical measurement, and interest in systems of healthcare, whilst introducing the equivalent of a cultural turn (Barnett, 1998) which values greater critical engagement with constructs such as place and wellbeing. What Kearns and Moon (2002) choose to interrogate as a process of subdisciplinary change is part of a necessary and natural formalisation of emergent ideas, and “novelty”, in a discipline that required greater contestation of, and enquiry into, the development of knowledge.

Dorn et al (2010) relate the feeling of discomfort that the exclusiveness of divisions which historically existed within medical geography causes with respect to engaging with the discipline. They suggest that prospective health and medical geographers be aware of the “multiple origins, interpretations, and affiliations” (Dorn et al, 2010 p.56) that working in health geographic research entails. Carried through this thesis is a realisation that numerous narratives within geography, and further afield, are important to understanding the subject matter. As will become apparent, the core stanchion upon which the thesis is built is an understanding, and analysis of healthcare systems; this analysis is conducted within a quantitative framework and executed using geographic information systems (GIS). However, it is apparent that such an approach should not be a closed door to considerations of the importance of place, policy and social relationships.

1.1.2 Geographic Information Science and Spatially Integrated Social Science

A geographic information system (GIS) is a computer tool for storing, processing, representing, analysing and visualising geographic information (Longley et al, 2011). However, the successful and relevant use of GIS in an analytical, problem solving capacity requires geographic information science (GISci)- a scientific framework for GIS, which supports the methodological assumptions of transparency, objectivity, and reproducibility (Longley et al, 2011; Goodchild, 1992; Goodchild, 1990).

This thesis uses a number of quantitative geography and GIS techniques under the broad remit of GIScience, augmenting the locational characteristics of public health data in order to derive a better understanding of access to healthcare services, and the patterning of local provision of healthcare. Cromley and McLafferty (2002) suggest that it is only since the 1990s that GIS has been used with any regularity in health research, with the growing number of studies suggesting that it is still an emergent field of enquiry; although, there is a longer history of quantitative health research that involves location in the medical geography history (Meade and Emch, 2010). Health and epidemiologic research has long valued the importance of space, however the challenge of working with geographic information means that use of GIS is not as ubiquitous as it might be. This challenge is encountered both in practical terms: accessing data at a suitable spatial resolution, adding location to tabular data; as well as on a more conceptual level, in harnessing the ability to think spatially.

Janelle and Goodchild (2011) underline the value of using GIS in interdisciplinary settings (see also Goodchild and Janelle, 2004). They reason that space is one of the few unifying themes shared by social science disciplines, and that a systematic approach to space is important “to a deeper understanding of social and environmental processes” (Janelle and Goodchild, 2011 p.28). This is because location acts as a link between often disparate information. Key to integrating a systematic spatial basis for analysis across social science disciplines is establishing the conceptual foundations for spatial thinking. This requires a formal approach (Schuurman, 2006) to geographic concepts if they are to be used effectively, including the understanding of challenging spatial ideas such as spatial heterogeneity and spatial dependence (Goodchild, 1986). Gatrell and Rigby (2004) echo this, expressing the genuine multi-disciplinarity of “public health”, and the “somewhat daunting task” (p. 367) that constitutes a spatial perspective on public health.

1.1.3 Health and Healthcare Equity

Asthana and Gibson (2008) define both health equity, and healthcare equity, suggesting a distinction between the two terms. Health equity is the condition of “equal opportunity to be healthy” whilst healthcare equity is based upon “equal opportunities of access [to healthcare] for equal needs” (Asthana and Gibson, 2008 p. 4). In terms of providing healthcare services, healthcare equity tends to be the point of reference, as health equity is too abstract, and

better operationalized within a health promotion framework. The World Health Organisation (WHO) clarifies this distinction, elaborating upon the importance of need:

“Above all, on humanitarian grounds national health policies designed for an entire population cannot claim to be concerned about the health of all the people if the heavier burden of ill health carried by the most vulnerable sections of society is not addressed. The bias against these social groups in the provision of health care also offends many people’s sense of fairness and justice once they learn of its existence.” (Whitehead, 1992 p.432)

Thus the key criteria are set out as: equal access to available care for equal need; equal utilisation for equal need; equal quality of care for all (Whitehead, 1992 p. 436). Measuring need for healthcare is one of the most contested areas of research into population health and healthcare services, and hence synthesising a measure of equity from this is tremendously difficult. Increasingly, the tension between healthcare provision and need is highlighted by growing evidence for the veracity of health inequalities (Marmot Review, 2010). To this end, studies have focussed on observable changes in a practitioner defined healthcare equity through “monitoring” studies (Braveman, 2003) which focus on positive relative changes in the short term, using clinical indicators, quality measures, and patient demographics. Whilst healthcare systems set an aspirational, absolute condition of equity, assessing equity as an absolute is a strict impossibility. For this reason this thesis does not tackle equity in its fullness, instead focusing upon its geographic components, and using these to speculate about social justice more broadly.

Braveman and Gruskin’s (2003) attempt at defining equity in health rests on the principle of “distributive justice”, reflecting Harvey’s (1973) classic definition of social justice as “a just distribution justly arrived at” (p. 16). This thesis favours geographers’ approaches to social justice and injustice (Dorling, 2010a; Smith, 1977; Harvey, 1973), privileging the spatial component of equity as a result. More realistically, therefore, the consideration of equity in healthcare in this thesis pertains to “spatial equity” which Talen and Anselin (1998; see also: Truelove, 1993) offer succinctly as “the question of who benefits and why in the provision of urban services and facilities” (p. 596) in light of Smith’s mantra “Who gets what, where, and how?” (1977).

Undoubtedly, research into healthcare will always have at its core the issue of social justice, or equity. However, the scope of what equity means can be a limiting factor in seeking to advance research. For this reason, this thesis acknowledges the practical and rhetorical

significance of healthcare equity, whilst also focusing on its geographic manifestations. In this way the focus of this thesis rests on characterising access to healthcare services, the spatial patterns of registration or utilisation, and their intertwined geodemographics – the study of people by where they live (Longley et al, 2005).

1.1.4 Access to Healthcare

Provision of healthcare services is undoubtedly a geographic problem; healthcare, be it primary care through general practice (GP) surgeries, or secondary care in hospitals and other treatment centres, has to be provided somewhere, and on that basis spatial accessibility is a crucial component of a patient's experience. Further, as Barnett and Copeland (2010) show, health systems are under increasing pressure to meet demand for health needs which have arisen as a result of social factors such as changing population age structure, and factors such as the obesogenic environment. Access in both a practical and an affective sense is driven by an understanding of the local contexts for provision, and failure to account for these effectively can have profound impacts upon fairness, social justice and healthcare equity.

The dominant understanding of access in healthcare research involves the spatial interaction between a patient and a medical professional (Ricketts, 2010). Aday et al (2004) position this oppositional spatial interaction form of access as fundamental to both fulfilling policy requirements, as well as contributing to the health of individuals. This is reflected in the observed existence of inverse care laws in systems of public healthcare provision, in which the availability of healthcare services varies inversely to the need for those services (Hart, 1971). Cromley and McLafferty (2002) reiterate Aday and Andersen's (1974) five dimensions of accessibility: availability; accommodation; affordability; and acceptability. Availability and accessibility deal with locative aspects of access – whether enough services exist in an area in order to meet local needs, and whether they are suitably located so that the local population can visit them. Accommodation asks whether the available services do in fact meet the needs of the population, whilst affordability and acceptability question whether a patient can pay for services, and whether they are satisfied with those that they are provided with.

Joseph and Phillips (1984) privilege the geographic proximity component of accessibility, with distance to nearest and utilised services representing potential and revealed accessibilities, effectively contrasting the opportunity to access a healthcare service with the

realised access. Others highlight the value of the healthcare system (Thomas, 1992) as a whole in facilitating access, as well as the organisation and stratification of space (Knox, 1978). There are several other ways of characterising access: Hawthorne and Kwan (2011), for instance, introduce affective perceived distances into their measure creating local variations in access by the differing acceptability of services to patients, whilst Ricketts (2010) discusses access as the “fit” between the needs of the patient and the healthcare system’s attempt to meet those needs.

This thesis applies both distance-based and non-distance-based measures of spatial accessibility to healthcare services, using patient and provider characteristics to unpick the observable geodemographic differences in patients accessing healthcare. Rather than focus on the potential of people to access healthcare, the focus is instead upon patient behaviours, and whether the observable differences in access characteristics of different population groups are attributable to the local provision available.

1.1.5 The National Health Service

The UK operates the National Health Service (NHS) system of universal healthcare; although this is in practice four distinct institutions covering England, Wales, Scotland and Northern Ireland. Henceforth when this thesis refers to the ‘NHS’, it is referring to NHS England, which provides the broader contextual basis for the research.

The NHS operates on the basis of “universal service”, implying that every eligible individual is entitled to receive a baseline standard of care. Since its inception in 1948, and most recently reflected within the NHS Constitution (DH, 2010a), the comprehensive service provided by the NHS is aimed at being “available to all irrespective of gender, race, disability, age, sexual orientation, religion or belief” (p. 3). Further, clinical need is the basis for receiving NHS service, not whether an individual can pay for it; the NHS is free at point of contact and its funding is provided through taxation, in part via a “national insurance” contribution. The NHS constitution (DH, 2010a) makes a number of further “pledges”, which amount to legal rights: of access to healthcare services, and to drugs and treatment; to quality of care; to confidentiality; and to choice and involvement in healthcare.

Gorsky (2008) reminds us that there is no “unitary” narrative which defines the developmental trajectory, successes and shortcomings of the NHS, but that its historiography reveals important, thematically distinct periods. These are primarily politically

motivated, and consider the effect of structural reorganisations and socio-economic conditions (such as austerity) in the UK on the NHS, its employees and its patients; these are necessarily complex, however “[a]t its crudest the dominant story of the NHS today is of a fairly stable institution in its early decades, which then entered a period of sustained reform characterised by the incursion of market disciplines” (Gorsky, 2008 p.440). This thesis deals with an NHS that is again in transition: using data shaped in the era of “New Labour” it attempts to characterise the recent circumstances that local areas find themselves in, prior to proposed reforms, with respect to healthcare.

The scale of the NHS is enormous: it employs more than 1.4m people, treating c. 3m people per week (NHS, 2011) out of a population of an estimated 52.7m in England (ONS, 2011). This commitment requires an unprecedented level of spending by government which is matched only by spending on pensions and welfare, and constitutes over twice the spending on defence (HM Treasury, 2010). Such is the political significance of the NHS that the current UK Government has pledged to increase total NHS spending in real terms in each Parliamentary year (HM Treasury, 2010 p. 6). However, cost saving in a number of areas is deemed essential and this has in part led to proposals for significant reform of the NHS, which is documented in the 2010 “equity and excellence” White Paper (DH, 2010b). The content of the reform agenda is discussed at length, where pertinent, later in this thesis.

1.2 Aims and Objectives

In *exploring the provision of local healthcare services* there are several aims, the principal of which is to better understand what underpins the variations in spatial interaction between different population groups and their local healthcare providers. The secondary aims derive from the principal aim: contextualise the geometric and social circumstances of patient registration with healthcare services; effectively implement the use of patient names in order to classify the ethnic, linguistic or cultural origins of the patient population using the Onomap typology; and demonstrate the value of GIS to the analysis of healthcare services. The key foci are patient geodemographics and access to services, seen through quantitative analysis. The objectives to be met by this thesis are as follows:

- 1) Augment and enrich spatial healthcare data for fine scale analysis by exploiting address registers and classification.
- 2) Explore the representation of spatial information for use in healthcare research.

- 3) Explore the validity of a normative model of primary care registration with the observed catchments served by General Practitioner (GP) surgeries.
- 4) Explore different models of characterising primary care registration.
- 5) Synthesise modelling approaches in order to better understand patient primary care registration behaviours.
- 6) Explore opportunities for further detailed spatial analysis of healthcare services.

These objectives, as well as other point of interest are covered over the following 8 chapters. The specificity of some of these objectives around the ideas of modelling and representation might lead one to believe that this is a particularly methodologically focussed PhD: however, the intent is also to practically explore the notion of spatially integrated social science. The novelty of some of the data used in this thesis, which arises from privileged right of access, is such that it may be unique in academic terms, and shifting administrative responsibilities in the NHS are unlikely to make them readily obtainable for the foreseeable future. In this way, a more holistic approach is attempted; the context of the thesis is first and foremost spatial in nature, but in the application of spatial analysis and quantitative geographic techniques an effort is made to associate processes and outcomes with the political and social dimensions that underpin study of healthcare and geodemographics.

1.3 Funding and Ethical Context for the Thesis

This PhD is a “collaborative award in science and engineering” (CASE) studentship, funded principally by the Economic and Social Research Council (ESRC) and partly by Southwark Primary Care Trust (PCT). The responsibility of Southwark PCT is to commission primary, community and secondary care from the relevant providers: effectively they constitute the local management of healthcare. However, the implementation of proposed NHS reforms, which anticipated the abolition of PCTs (DH, 2010b) meant that a number of the functions of Southwark PCT have been arranged into clusters in order to derive management cost savings that can instead be invested in frontline care (Southwark PCT, 2011a). The Department of Health (2011a) sets out PCT clusters as temporary bodies aimed at dealing with the likelihood that PCTs on their own will not be able to maintain effective management capacities up until the point of their abolition in 2013. In addition, PCT clusters are intended to give space to GP Consortia to develop their commissioning responsibilities. The new cluster – NHS South East London – includes Bromley, Greenwich, Lambeth, Lewisham and Southwark Primary Care Trusts and Bexley Care Trust.

Ethical approval for the study was granted by Bromley NHS Research Ethics Committee, the local research ethics body. In addition to this, the author had to submit to a Criminal Records Bureau (CRB) check in order that an honorary research contract with the NHS could be issued. This entitled the use of patient identifiable data under special conditions which defined the secure use, and storage of the data. Upon the conclusion of this PhD research, the data will be destroyed using specialist software in line with the agreement on secure use of data. The additional supply of an extract of hospital episode statistics (HES) data was also subject to ethical approval, granted through the NHS Information Centre, and again due for destruction upon the expiry of the data license.

1.4 Thesis Structure

This thesis is organised into nine chapters. Seven core analytical chapters follow this introduction, with a final chapter of discussion concluding the thesis. Table 1.1 highlights where each objective from section 1.2 fits in the context of the broader thesis.

#	Chapter Title	Objective
1	Introduction	
2	A Spatial Data Infrastructure for Healthcare Planning	1
3	Representing Healthcare Information	2
4	Ethnic Segregation and Structure in Southwark, London	2
5	General Practice Surgery Patient Register Composition in Southwark	2, 3
6	Patient Characteristics and GP Surgery Service Areas in Southwark	4
7	Patient Primary Care Registration Behaviours in Southwark	3, 4, 5
8	Operationalising Health Data for Hospital Trusts	2, 6
9	Discussion, Conclusions and Prospects	

Table 1.1: Thesis structure by chapter and corresponding objectives.

Chapter 2 – “A Spatial Data Infrastructure for Healthcare Planning” – considers the conceptual and practical implications of dealing with healthcare data. Initially, the idea of a spatial data infrastructure (SDI) is outlined, and evidence for its application to health data is discussed including changes in the way that the NHS creates and uses its data.

Subsequently, the Southwark primary care trust (PCT) patient register is introduced, and the specifics involved in preparing it for use in the analytical Chapters 4 - 7 are elucidated.

Finally, the Hospital Episode Statistics (HES) data explored in Chapter 8 are summarised. As a whole, the chapter highlights the inadequacies of current NHS data practices, advocating greater thought, particularly in terms of spatial dimensions, in future policy, counterpointing

this with an examination of the labour that goes into preparing NHS data currently for use in spatial research.

Chapter 3 – “Representing Healthcare Information” – looks at the GIScience background to working with healthcare information. It elaborates upon the theory of representing information within a quantitative framework, and considers where this overlaps with locative approaches to health and medical geography. Using this context, a set of established “potential” model approaches to spatial equity and access are examined. This both highlights the usage of different representations of spatial health information as well as introducing the primary study site for much of the research in this thesis – the London Borough of Southwark.

Chapter 4 – “Ethnic Segregation and Structure in Southwark, London” – acknowledges that the Southwark patient register has the potential to be an important resource for social research beyond the scope of health research. In this vein, a broader picture of ethnic residential segregation is developed using the Onomap classification (Mateos et al, 2011) of cultural, ethnic or linguistic origin, which classifies individuals based upon their names. Several existing quantitative approaches to capturing dimensions of ethnic residential segregation are discussed, and the Southwark context is outlined in terms of traditional indices of segregation. Subsequently, a novel graph-based depiction of ethnic residential segregation is demonstrated, and its variation across different spatial aggregations – in what is known as the Modifiable Areal Unit Problem (MAUP: Openshaw, 1984) – is explored.

Chapter 5 – “General Practice Surgery Patient Register Composition in Southwark” –explores the actual distribution of patients by GP surgery of registration in Southwark, utilising both network distance and public transport (bus network) travel time in order to do this. Having also discussed the historical basis for normative models of spatial structure, the particular importance of Central Place Theory, optimisation approaches to locational analysis, and the use of normative models in healthcare is broached. The remainder of the chapter outlines a normative approach to shaping GP surgery “market areas” by solving the transportation problem using linear programming, which is modelled on the basis of an extremely detailed definition of spatial structure in Southwark.

Chapter 6 – “Patient Characteristics and GP Surgery Service Areas in Southwark” – develops a “service area” approach to looking at registration, explaining that in a service dense inner-

urban area such as Southwark, a market area approach is ineffective as it does not allow for an overlapping of market area boundaries. Thus an approach which does allow for the possibility of overlap in the depiction of each GP surgery's area of service is developed, based upon techniques used for delineating point patterns in ecological analyses of animal home ranges. Univariate analyses are conducted on these service areas to reveal different patterns in local GP surgery registration by different ethnic groups.

Chapter 7 – “Patient Primary Care Registration Behaviours in Southwark” – brings together the previous two chapters in order to explore the current policy surrounding patient choice in primary care. Initially, the implications of GP surgery defined “catchment areas” are explored, using the catchments previously defined by Southwark GP surgeries in collaboration with Southwark PCT. Subsequently, an attempt is made to derive a geodemographic understanding of patient registration behaviour, using constrained and unconstrained distance and time travel measures highlighted in Chapter 5, and an indicator of local provision of healthcare from Chapter 6. The analysis is carried out using both standard logistic regression, and multi-level modelling. Whilst the multi-level approach is a promising development, it raises some computational issues with regard to its application in this thesis.

Chapter 8 – “Operationalising Health Data for Hospital Trusts” – acknowledges that another major revision to the operation of the NHS concerns a reinvigorated approach to some aspects of competition – previously softened to a cooperative approach under New Labour. Moving on from a detailed analysis of local primary care provision in Southwark, this chapter explores the validity of shifting scales, investigating patterns of admissions to hospital care. The spatial extent of NHS acute trust, and foundation hospital trust, service areas in Greater London are assessed using the modelling approach discussed in Chapter 6. This exploratory analysis raises questions regarding the possibility for competition between trusts in the provision of inpatient and outpatient services.

Finally, Chapter 9 concludes the thesis with a discussion of evidence developed in the thesis as a whole. The themes highlighted in section 1.1 are revisited, before promising areas of enquiry for future work in this area are highlighted.

2 A Spatial Data Infrastructure for Healthcare Planning

2.1 Introduction

The application of Geographic Information Systems (GIS) to the analysis of public health data is a valuable component in the understanding of a wide range of concerns in health and healthcare. Cromley and McLafferty (2002) outline the potential for using GIS in numerous contexts including: assessing 'at risk' populations; contextualising a patient's 'environment'; describing inequalities in health outcomes; revealing patterns of health service utilisation; and locating health services. However, Cromley and McLafferty (2002) also make it clear that "the success of health-related GIS projects depends on having access to accurate, timely, and compatible spatial data" (p.67). Accessing health data in the UK involves negotiating a variegated set of data resources, and often requires the submission of data requests in order to access data at an appropriate spatial scale. With the NHS lacking a unified approach to data dissemination, and very limited integration of spatial information, constructing an effective repository of health, contextual, and infrastructural data is a difficult and time consuming process which represents a major investment in the specific research undertaken. Data sharing in the NHS, particularly with respect to Primary Care, is a limited practice owing to fiscal as well as institutional factors. Data quality is often a compromise between considerations such as: privacy and ethical directives; which data are actually collected and how they are managed; expense and availability; and the possibility of integrating or augmenting the data subject to other datasets.

This chapter begins by considering NHS health data in the context of spatial data infrastructures (SDI) and the movement towards free and open data. Subsequently it introduces the Southwark patient register, with its role as a source of primary care registration data considered in detail. The Southwark patient register data is augmented through application of: address geocoding; household definition; coding ethnicity by patient forename and surname; and the application of a household life-stage classification. The integration and augmentation of the data in this way adds additional power of description and analysis. Limitations to the methodologies are considered throughout, allowing a weighing of the relative merits and uncertainties inherent in the use of the procedures. Hospital Episode Statistics (HES) data, considered here as a conventional data source, are

used in this thesis to consider the linkages between patient referrals, patient choice and their spatial patterns. HES analysis entails linking data with spatial areas, as well as reclassifying aspects of the data such as the primary diagnosis field – a detailed report of disease diagnosis coded by the International Classification of Diseases (ICD-10).

The overriding motivation for this chapter is to set out the conceptual and practical technicalities of dealing with health data. However, it is necessary to frame this intent within the broader discourse discussed in Chapter 1. Developments in Health and Medical Geography have led to the increasing visibility and value of *place* in research. Place is an uneasy concept within the quantitative social sciences because it is often perceived (assuming place is understood to be socially constructed in some manner) as inherently unquantifiable, and those elements of it that can be captured must be formally encoded in a consistent manner (Goodchild, 2011). For the purposes of this thesis, “place as context” (Goodchild, 2011 p. 28) is the most desirable interpretation of place as it allows the linking of individual behaviours to contextual elements to do with an individual’s household, neighbourhood and/or community. Health data such as the Southwark patient register, or HES, have a wealth of potential to contextualise patient behaviours through deriving households and considering their composition and context, or looking more widely at linking incidence of hospitalisation through referrals to small area units and statistics.

2.2 A Spatial Data Infrastructure for Health Data

2.2.1 Introducing the Spatial Data Infrastructure

Masser (2005) suggests that for the benefits of GIS to be brought to bear, “governments will have to regard geographic information as an asset that needs to be carefully managed” (p.7), and links this management agenda to that of creating an infrastructure. Such an infrastructure is required in order to both promote the diffusion of GIS technology, and facilitate data availability and access. In consequently formalising the Spatial Data Infrastructure (SDI) concept, Masser identifies 4 key elements:

- 1) Maximise the use of geographic information, by facilitating access to as much as possible across a wide range of public and private stakeholders.
- 2) Coordinate action across all government departments and functions.
- 3) Support effective decision making by allowing SDIs to be user driven.

- 4) Manage a wide range of activities involved in implementing a SDI:
 - Technical: data, technology, standards, delivery.
 - Organisational: financing, human resources.

(adapted from Masser, 2005 p.17)

The UK has innovated two previous SDIs, the “National Spatial Data Infrastructure” and the “giGateway”, both of which have been successively decommissioned in favour of the new “Discovery Metadata Service” (Defra, 2010) which implements the UK location strategy and INSPIRE. The UK location strategy (DCLG, 2008) sets its objective at maximising “the value to the public, government, UK business and industry of geographic information” (p.6) whilst acknowledging:

“Currently, too few government-owned datasets that incorporate location can be easily assembled and analysed with reliability from across local and central government bodies. There remains too much duplication, too little reuse and too few linkages across datasets which are required to support policy implementation in, for example, planning, housing, flooding, social exclusion and traffic management” (p.6)

The UK Location strategy is intended to dovetail with the INSPIRE (INfrastructure for SPatial InfoRmation in Europe) directive, a general framework for implementing a SDI laid down by the EU in 2007. Primarily INSPIRE is aimed at the natural environment, but it does incorporate some consideration of health in terms of the impacts of environmental disamenities on human health and safety (INSPIRE, 2011).

Increasing use, and sophistication of online, web-based, services are redefining the way that geographic information is being collected, stored and disseminated, leading to the current shift to the “Discovery Metadata Service”. The new focus is on operationalising the relevant standards set out for information with attached location (geographic information), and supporting the creation and publication of the appropriate documentation, or metadata (the data about the data), to enable effective usage of the data in question. A clear distinction is made between the data provider and the data publisher (Defra, 2010) due to the rise of communal government data repositories such as data.gov.uk and data.london.gov.uk. A data provider is the organisation with whom the data originates and it is their responsibility to supply the data and appropriate metadata for publication; a data publisher simply publishes the data, supplying data services to users. The creation of metadata has often been neglected, and seen as a retrospective action to be achieved once data has been

made available; the new structure is thus an attempt to increase transparency and the general usefulness of data.

This bipartite approach to creating and documenting data (on the one hand) and disseminating data (on the other) is in theory a boon to research. Websites such as data.gov.uk are part of a wider movement toward open government data which seeks to bring together data in one place and in a linked and easily searchable form. Much of this movement results from the “power of information review” (Mayo and Steinberg, 2007) and the subsequent “power of information taskforce” (POIT, 2009) which calls for action in six key areas including: “freeing up the UK’s mapping and address data” and “ensuring that public sector information is made as simple as possible for people to find and use” (p.4). This approach acknowledges that innovation in accessing data and information are the lifeblood of the knowledge economy; former Prime Minister Gordon Brown, in a speech on “Building Britain’s Digital Future” (22 March, 2010) stated:

“We are determined to go further in breaking down the walled garden of government, using technology and information to provide greater transparency on the workings of Whitehall and give everyone more say over the services they receive.” (Brown, 2010)

Tackling spatial inequalities in health and healthcare, such as the social gradient in health outcomes demonstrated in “Fair Society, Healthy Lives” (The Marmot Review, 2010), or the inverse care law (Hart, 1971), requires sufficient access to the right kind of spatial data, much of which is output by the government and its various bodies (notably in Great Britain by the Ordnance Survey (OS)). Evans and Kalra (2005) acknowledge that “the need for national infrastructures to share health information has become a major political issue in most developed countries”. Thus, having in place a Spatial Data Infrastructure that facilitates ease of access to authoritative government geographic information is essential to conducting timely, effective and informative health and healthcare research. In the next section, the ways in which these more general structures and trends apply to health are considered.

2.2.2 Spatial Data Infrastructures and Health

Ingram et al (2006), in giving healthcare information infrastructure an international treatment, state that “historically, the healthcare system has not made effective use of information technology” (p.17). They suggest this owes much to the complexity and uncertainty involved in effectively managing healthcare. Certainly, long-term strategies have

to be in place to manage the medical records of patients across their life-course, however such strategies are constantly subject to the effects of reform and changes in political circumstances affecting the system as a whole. In the NHS, keeping effective charge over the records of over 50 million people is a daunting prospect and one that cannot simply be amended and upgraded in an ad hoc fashion; interoperability, confidentiality, and technological obsolescence have to be effectively governed (Ingram et al, 2006). To this end, GIS and spatial data, as an emergent theme in health research and practice, may simply have missed the last upgrade cycle (i.e. in the NHS the previously paper-based records for primary care were computerised in 1991). The question remains however, what place do spatial data have in the future of health care information and how might they be deployed?

Health is cited by the UK location strategy (DCLG, 2008) as a key area within which policy and operational benefits can be obtained through use of geographical information, with the example of emergency response by ambulances given as a practical example. However, the extent to which researchers, policy makers or practitioners have explicitly invested in SDIs as a useful framework for health information is rather limited, with interest instead focusing on local information management. Within the various spatially disaggregate bodies that are responsible for healthcare delivery (such as Primary Care Trusts (PCTs) in the NHS) policies on information also face the competing criterion of keeping private data private. Despite this, both Boulos (2004) and Ingram et al (2006) suggest that building a health information infrastructure from the bottom up is preferable to the imposition of a centralised control structure that foregoes existing local data management practices.

Boulos (2004) is one of the few who has published on spatial health information infrastructure with particular reference to the NHS. He sees SDI as imperative if health analyses with GIS are to go beyond "time-limited, single, isolated aetiological research or surveillance issues processing retrospective data" (p. 2). Higgs and Gould (2001) pointed to a situation in which the analytical use of GIS by academics had outstripped the operational deployment by the NHS; even now, 10 years on, GIS receives limited attention in the NHS outside of basic map-making functions as a few PCTs strive to publish local "atlases of health" which document diagnoses and health outcomes for their jurisdictions at small area levels. Cockings et al (2004) confirm that barriers to the widespread use of GIS in health services are cause of concern, but that awareness is rising within the health community.

Under the previous Labour government in the UK, the Wanless Report (2002) called for a national reinvestment in information technology, having inherited a NHS information technology plan dating from 1992 that was responsible for the then limited scope of NHS information resources (Cross, 2006). In line with the Labour government's focus on evidence for the success (or failure) of NHS policy, and the proliferation of quantitatively-based targets to assess quality in the NHS, recommendations for a new NHS infrastructure focused on a national scale, centralised, single system implementation. Connecting for Health (CfH) was the NHS body responsible for maintaining and developing this infrastructure, but time and budget overruns in the project, known as the "National Programme for IT", led to the current Conservative coalition government making it one of the first in its recession-influenced cuts. However, the need for effective health information infrastructure persists, and the NHS white paper "Equity and Excellence: Liberating the NHS" (DH, 2010b) has spawned a response purporting to deal with the "information revolution" (DH, 2011b). In line with the decentralisation that the NHS (DH, 2010b) is pursuing by way of the transfer of primary care commissioning to consortia of GPs, and the dissolution of the hierarchical structure to provision; IT is set to be developed using a bottom-up approach too.

NHS proposals currently surround the integration nationally of the vast array of locally managed datasets in a connected and joined up way, a distinct shift from the previous attempts to impose a single, common, centralised system. Like much of the rhetoric supporting the wholesale reforms to the NHS, the patient is set squarely as the focus and reason for the proposed information infrastructure, reportedly leading to greater engagement and, crucially, furthering patient choice. Further in evidence is the movement towards open and free data, with the view that:

"The information revolution depends on a 'presumption of openness', which will mean routine publication of aggregate datasets built-up from data held securely in people's records." (DH, 2011b p.11)

Whilst it is unclear how a "presumption of openness" objectively differs from mere "openness", the NHS has encapsulated the general framework in Figure 2.1. In this representation, it becomes clear that research practices are seen as important to tackling health inequalities and operational factors influencing the effectiveness of the NHS. As the "information revolution" is under consultation, unfortunately the practicalities of what a

health information infrastructure will look like, let alone whether it will incorporate geographic information, remains to be seen.

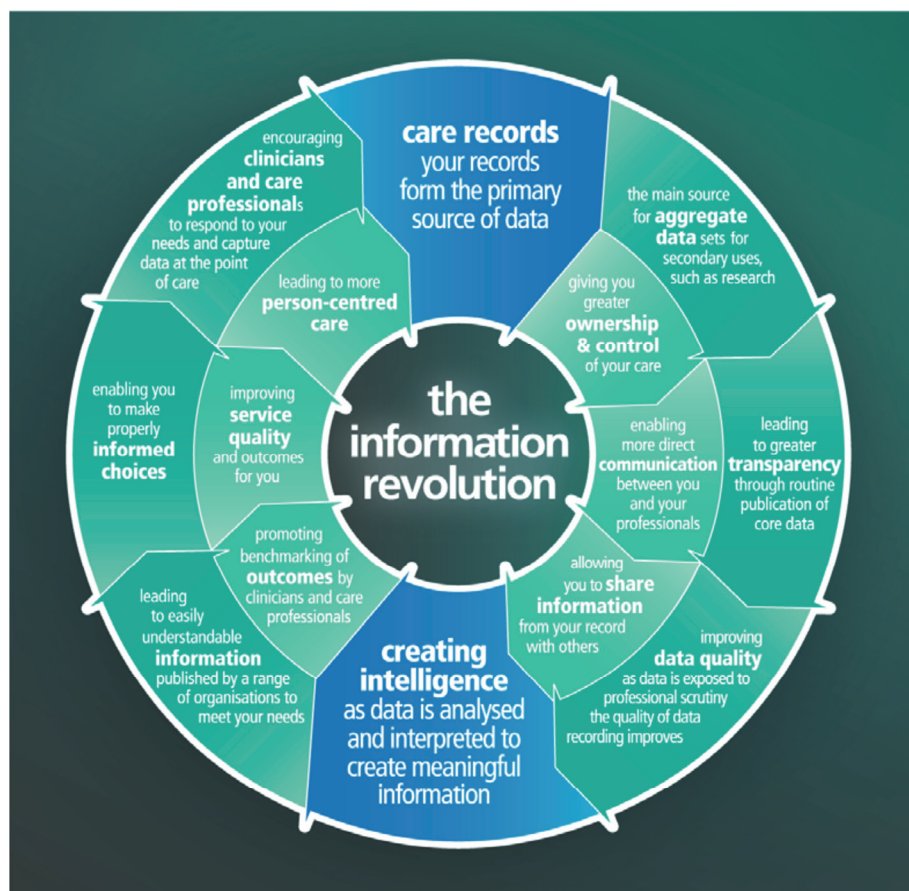


Figure 2.1: Wheel-like representation of the NHS information revolution (DH, 2011b p.12)

In line with the contemporary underpinnings of a (spatial) data infrastructure, whilst it is the government who decide upon the NHS policy, it is the NHS that implements it and they do it (for the purpose of research) by and large in a manner consistent with that discussed in the previous section: the NHS Connecting for Health body facilitates the creation and documentation of data at a local scale through the use of IT infrastructures and associated practices, whilst much of the data is disseminated through the NHS's public facing data repository the "NHS Information Centre" (NHS IC). The existence of the NHS IC is key in explaining the relative lack of health data in the government's data.gov.uk site, with the NHS instead choosing to marshal its own data. In many respects this is a valid decision in light of the complexity of the health data available as holdings include multiple time-series, across multiple output geographies for numerous datasets, most notably hospital episode statistics (HES). The NHS IC also links a lot of (particularly Census 2001) data from the government "Neighbourhood Statistics" website, one of the few government websites which actually

seeks to integrate geography, particularly UK Census administrative geographies, with other data outputs. However, the “neighbourhood” level approach implied by the website name means that it is considerably more difficult to look at national spatial trends unless non-government resources are used such as the “Census Profiler” (www.censusprofiler.org) an academic project funded by an ESRC Census development grant (Figure 2.2).

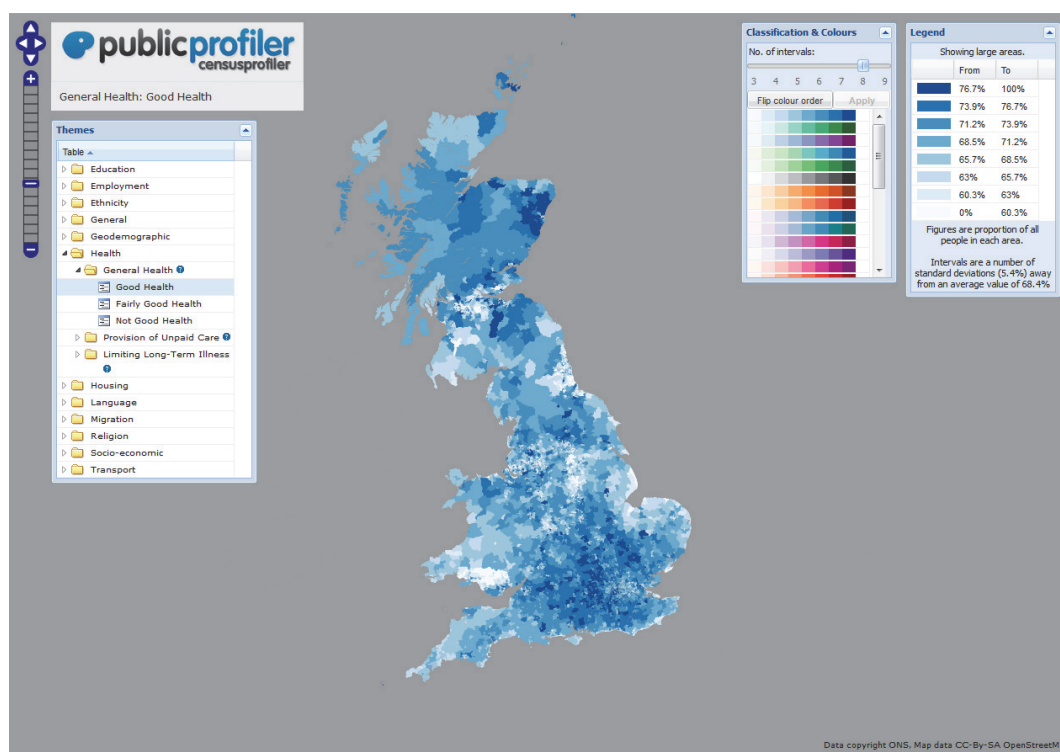


Figure 2.2: “Census Profiler” web mapping site showing proportion of people in areas reporting good health

If the NHS has been slow to adopt a consistent infrastructure for tabular health information, and take up of web-mapping with even the most high-profile UK government datasets has been slow (although crime is a notable recent exception), and reliant on non-government volunteers and academics, there can be little surprise that the literature is anything other than anticipatory with regard to health. Croner (2003) makes great play of the potential offered by “Public health, GIS and the Internet” and seeks to realign the SDI concept as a “geospatial one-stop” (p.70) as part of the broader “e-Government” agenda in the US. Nonetheless with the continued non-existence, or inadequacies, of a robust SDI it is unclear how the internet will best facilitate access to health information, and whether attempts to involve complicated geovisualisation and dissemination ideas will confound the simple underlying need for easily-accessible, timely, open and free health-information.

Fundamentally, research and analysis in health and healthcare is extremely complex. Creating an infrastructure which is as robust now as it is required to be in the future is extremely challenging and made harder by the constant socio-economic and political flux under which health systems operate. This is particularly true of health systems that operate as part of a welfare state, as exemplified by the UK's National Health Service. The NHS does not implement an effective spatial data infrastructure at the moment, and has experienced significant difficulties and cost overruns attempting to implement a centralised information technology and data management system in recent years. Despite this, straightforward access to aggregated tabular data is available, although accessing data at a sufficiently spatially disaggregate scale often requires a bespoke report to be generated, and can incur both financial cost and ethical approval delays to the researcher. Generally, the provision of primary care data seems underserved, and with the increased shift in focus to a primary care led NHS, this will have to be addressed in the future. The proposed NHS approach to health information infrastructure seems to follow that advocated by Boulos (2004), Rushton (2003) and others, wherein local and community level data is joined together as part of a larger infrastructure, taking advantage of existing systems and procedures. It remains unclear, however, as to whether the perceived import, and integration, of spatial information in public health data amongst the academic community will filter through sufficiently to make SDIs a viable target for contemporary changes to how the NHS collates and serves data to the public, or to the research community.

2.2.3 Practical Research Implications

The impact of limited data access and linkage practices across a system such as the NHS puts pressure on individuals and research groups to invest time and effort in collecting together the often disparate datasets pertinent to health geography research onto a local system. The commitment of numerous health-related researchers, in the academic, private and public sectors, to creating and maintaining such databases adds up to a huge amount of duplicated effort and expertise that could be mitigated by better spatial data infrastructures further upstream. The acknowledged limitation in this respect seem to be the motivation for the consideration of "health informatics", the practice of local data-warehousing and data mining (Wan, 2006), as an important methodological consideration in the literature. This perspective also tallies with suggestions from the academy that a broader

SDI be built from the ground up, and is echoed by proposed NHS strategy under consultation.

Practically, the situation that presents itself with regard to this thesis, is the need to store data locally and integrate other data sources using common lookups, such as administrative codes for small area statistics, or by administering spatial join techniques. The primary concern in terms of this local data warehousing must be to obey the requisite ethical approval considerations with respect to protecting patient confidentiality. In principle this means keeping the data in a password protected database, and likewise on a fully secure computer that has up-to-date antivirus and firewall software, as well as hard-disk password protection. It also becomes important to keep any scripts that call database tables (and hence reference the database password in the code) for the purpose of analysis in secure folders. As health data are generally highly voluminous (particularly when dealing with individual patient data extracts, rather than aggregate data), it is preferable to use a Relational Database Management System (RDBMS) in order to maximise the efficiency of data selection. Throughout this thesis, data have been stored in a MySQL database, however recent advances in spatial databases, most notably through the PostGIS extension to the PostgreSQL RDBMS, have meant that in the future data can be stored alongside their specific geometry as part of a fully integrated system. In this thesis it has to be acknowledged that GIS has to be used as a secondary data management and integration tool in addition to use as a primary analysis framework.

In constructing an appropriate database it is not only appropriate to input the appropriate data, but also to ensure they have the requisite spatial references attached, for instance an aggregate area code: with this in place lookup tables can help manage aggregated data across datasets that are aggregated at different scales. Similarly, analysis of point patterns requires an affixed easting and northing (latitude and longitude projected onto a plane), which requires a systematic way of allocating a position in space to all applicable observations. In the following sections the specific datasets used in this thesis are explored, with explicit documentation given for how the data are augmented by deriving new variables to add value, and how they can be manipulated with respect to spatial location.

2.3 The Southwark Patient Register

2.3.1 Background to the Register

The Southwark patient register is a localised extract of the NHS Central Register (NHSCR). Since April 2009 the NHSCR has been managed by the NHS Information Centre and integrated with the Personal Demographics Service (PDS) database. The PDS underpins the existence of the NHS Care Records Service (NHS CRS), maintaining electronic care records for all NHS patients in England, as well as providing the data that form the basis for payments to GPs. Having been fully computerised in 1991 from paper-based records first collected in 1939, the NHSCR's purpose is to maintain a list of all persons registered with a GP surgery in England and Wales (DH, 2009a). The NHSCR "does not hold any clinical health record information or other sensitive data items such as ethnicity or religion" (DH, 2007) and thus its primary purpose is record linkage. It has, however found another significant niche as an indicator of population change and migration (ONS, 2010). Access to the NHSCR data at a level of spatial resolution suitable for the depth of enquiry intended by the research presented in this thesis is only available on a PCT by PCT (primary care trust) basis. Working with Southwark PCT as a researcher with an Honorary NHS contract has meant that an extract of the NHSCR for Southwark could be obtained, subject to rigorous ethical scrutiny and secure storage considerations that stem from the use of patient identifiable data.

Records in the NHSCR are passed from the point of registration, at a GP surgery, electronically through the requisite PCT to the NHSCR database. The main fields captured in the NHSCR are: Forename; Surname; Date of Birth; Sex; Address; GP to whom the patient is registered; Health Authority responsible; and Date of Registration. The accuracy of the database depends on patients reregistering with a new GP surgery when they move house or emigrate, otherwise patients can remain on the system for some time. The procedure for removal of a patient from a GP because of distance to surgery (as opposed to conduct-based issues) in the new GMS (General Medical Services) contract (DH, 2009b) states that if a patient moves out of a designated practice area they may be deregistered. On notification that a patient is no longer living within a suitable distance to the GP surgery, a letter (although an SMS text message is becoming increasingly common) is sent to the patient advising of the need to register with a new GP surgery. It is possible that an individual would simply move from an area and not register with a GP surgery in their new location; in this situation if the GP is not visited for 2 years, the patient is again sent a letter (or SMS) and

asked if they still want to stay with their GP surgery, if they do not respond within 30 days, they are deregistered as it is assumed they have either moved, or do not wish to remain registered. Unfortunately, patterns of registration and thus reregistration vary by age, sex, health need and ethnicity or cultural practice, and 'cleaning' and managing a patient list places a high burden on administration. As a result, the NHSCR seems to be subject to a high degree of registration list inflation.

An extract of the Southwark patient register was taken in May 2009, and that extract forms the backbone of this research. The specifics of the Southwark patient registration data mean that the dataset consists of: information on everyone living within the Southwark PCT boundary whether they use a Southwark GP or not; and information on everyone living outside of Southwark who uses a Southwark GP. Although it is noted that the data may be subject to some inflation, in terms of assessing uptake and choice in GP registration, it is useful to have all records, even if they are not current as all records are an indication of a choice of GP made by patients living in a particular location. This is, however, an impediment to forming households and attempting to interpret the household life stage; the NHS is making a significant effort to accurately record addresses in the NHSCR as it is believed that this will help GPs cut down on fraud, wherein patients sign up to multiple GPs in order to get multiple prescriptions for the same ailment. Attempts to match new patients with the Royal Mail's Postcode Address File (DH, 2010c), are most useful to the NHS for making deprivation payments to GPs and for patient screening and monitoring purposes, but also for demographic analyses of patients. Further specifics of the patient register will be dealt with as they are pertinent to enquiry.

2.3.2 Address Geocoding the Southwark Patient Register

Address geocoding is the process of attributing a spatial location to a known address (spatial reference) that has no explicit georeference. This is achievable in a number of ways, but most involve matching an a-spatial record in a table or database with a spatial record in a different table or database as in Figure 2.3, and for this reason the process is often called 'address matching'. Figure 2.3 demonstrates a straightforward exact match, however as will be evident later, this is unlikely to occur without some standardisation, or the application of fuzzy-matching techniques. In Figure 2.3 the patient is being matched to an address and given a spatial position as per the British National Grid system of eastings and northings - a 6 figure projected grid coordinate reference in metres. There is a large amount of research

in computational geography and more broadly, computer science, that seeks to create generalisable address geocoding systems. Davis and Fonseca (2007) discuss the varying considerations in standardising addresses given different standards across countries, however for the purpose of this research a specific structure for geocoding can be outlined given the urban UK context of Southwark. Thus the geocoding can be based around postal addresses which in the UK roughly manifest as a geographic filter, with the postcode standing as a useful starting element for step-wise refinement.

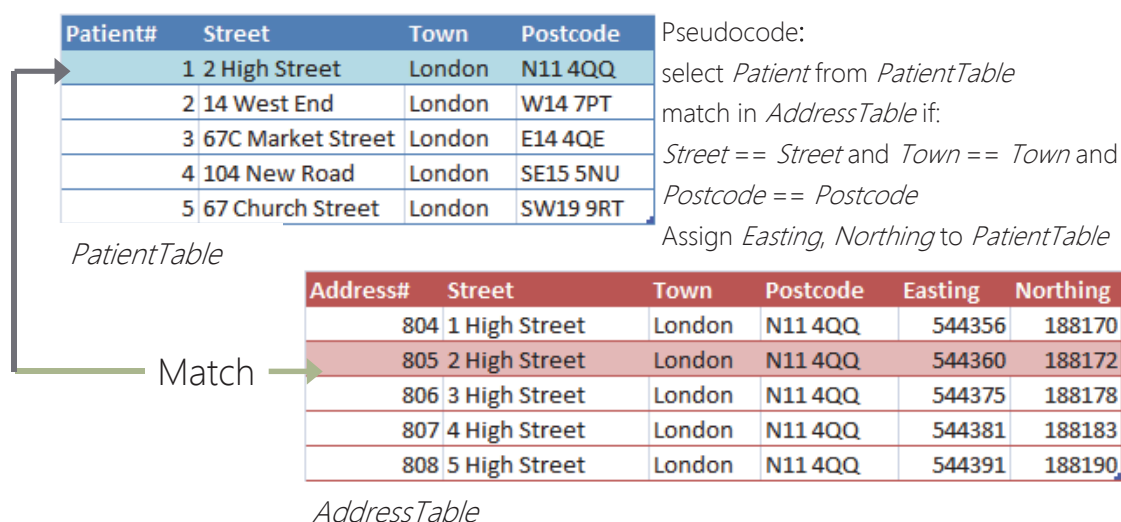


Figure 2.3: Basic schema illustrating address matching

Address-based data are often geocoded to the postcode centroid of the given postcode for each observation. This is a straightforward procedure because postcodes have a standard form and numerous geocoders exist to match an alpha-numeric postcode to a coordinate pair. In the academic sector the Mimas "Geoconvert" (<http://geoconvert.mimas.ac.uk/>) online service is particularly useful for this purpose. However, geocoding at the sub-postcode level is a significantly more difficult prospect: a street address is much more complex than a postcode, and such addresses originated prior to the innovation of postcode referencing between 1959 and 1974. Address referencing tends to proceed using the concept of a geographical filter, starting at the most discrete part of the address (the household), and successively moves to the more general street address, then the city, the county and finally the country if required. Further difficulty arises with the multiple ways in which a household can be conceived and so signified: as an independent property with a number, a name or an alphanumeric (i.e. 9A); as a flat or subdivided house that otherwise stands independently; as a flat within a block of flats; as a flat within a block of flats within an estate; and so forth. Whilst postcodes have an inherent robustness in their short length and

widely recognised form, addresses can easily be obfuscated through the inclusion of non-standard or composite information (Davis and Fonseca, 2007), including linear references (i.e. 100 metres along *x* street), place names and toponyms (i.e. reference by landmarks) or a combination (i.e. near/50 yards from *landmark*). Southwark also has a high cultural diversity, with a large immigrant population, to whom British cultural standards in address recording may be unfamiliar, and who may find accurately reproducing British street names and addressing-standards challenging.

There is a British Standard (BS 7666: 2006) governing how addresses are recorded in spatial datasets for gazetteer purposes (Morad, 2002). This gives us an address form that is detailed in Figure 2.4.

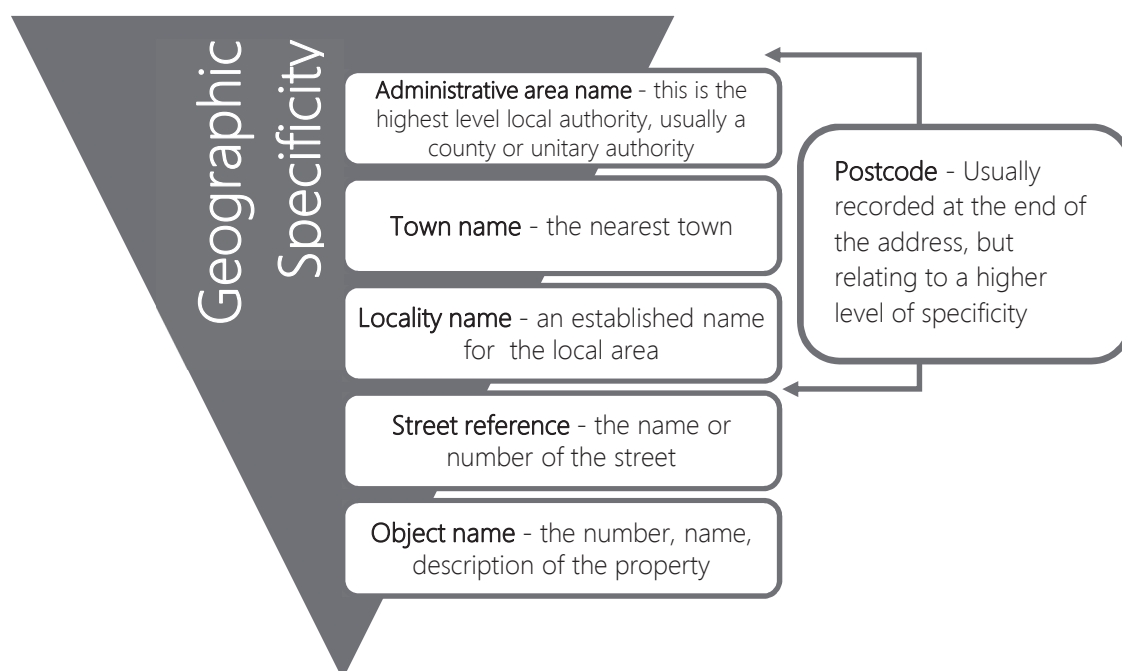


Figure 2.4: The geographic address filter adapted from BS7666:2006.

This is however open to some interpretation in the specific case of the London Borough of Southwark, which is landlord for the largest stock of social housing in London, accounting for 45,000 tenants (Southwark Council, 2011). The dense geographies of council estates often require additional specificity in the 'Object name' (Figure 2.4) reference, which is further divided into flats, houses and estates as in Figure 2.5. This leaves a complex situation for geocoding, as social housing that necessitates this level of address specificity creates: firstly, a lot more variables to account for in geocoding; and secondly, the practice of

truncation and abbreviation in order to fit the required information onto paper forms that may leave limited space for longer addresses.

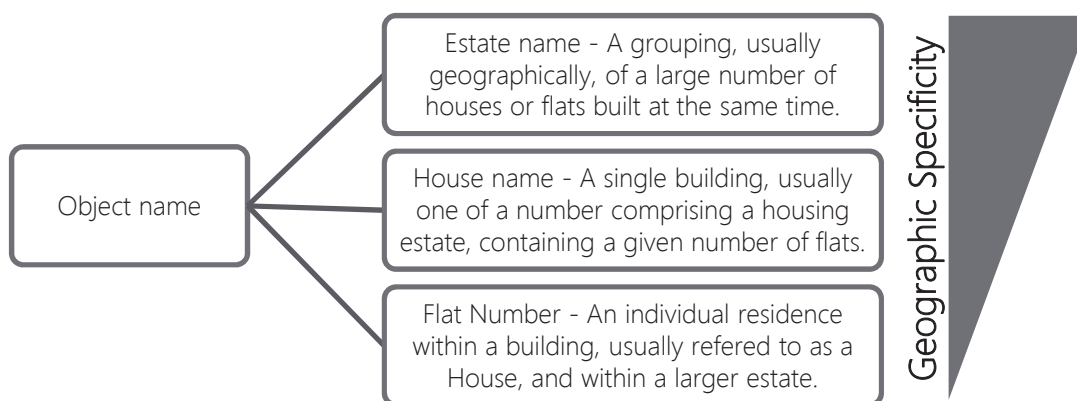


Figure 2.5: Stratification of 'Object Name' (Fig. 2.4) due to Social Housing.

The resultant situation means that geocoding any given address in Southwark could result, as demonstrated by Figure 2.6, from a very simple to a very complex address.



Figure 2.6: Hypothetical Address Complexity Issues in Southwark, London

Zandbergen (2008) notes that most addresses exhibiting some level of complexity will require a form of probabilistic record linkage, i.e. a process of matching records under conditions of uncertainty, often referred to as 'fuzzy matching' and requiring some form of address standardisation. This is in contrast to the assumptions of deterministic matching wherein records are assumed to be error free and can be matched with spatially referenced data through equivalence matches as demonstrated in Figure 2.3. The accuracy and efficacy of linking addresses, as a form of spatial reference, to a spatial location (or spatial position) comes under the banner of geocoding quality. This is a difficult, but necessary, element in determining the rigour and applicability of a geocoded dataset, as geocoding errors can adversely influence any subsequent results.

2.3.3 Assessing Geocoding Quality

Any geocoding that results from an address-matching process is only meaningful if it meets certain expectations regarding quality. Although Krieger (2003) states that requirements for precision will vary by study, there are some clear guidelines to quality that can be defined that follow a sense of scientific rigour. Zandbergen (2008) outlines three important aspect of assessing quality:

- Match rate - the percentage of records that produce a 'reliable match', as defined by the criteria set out in a geocoding process (how 'close' an address has to be to a known record before it is accepted as a match).
- Positional Accuracy - how accurate is the allocation of a position to the real location of the object in space? This question is effectively outsourced to the Ordnance Survey in the case of this thesis, as records are linked to addresses in an OS database in which every address is assigned a record of position represented by a single point, with an associated indicator of positional accuracy.
- Repeatability - As in scientific discourse, reproducibility is important in geocoding, Zandbergen (2008) discusses this in terms of difference between geocoding results from commercial vendors. Generally, it is essential that you be able to repeat a geocoding process for the same data and obtain the same results. This means handling addresses in a coherent and consistent way.

These aspects of quality in mind, it is clear that any errors in geocoding can derive from three sources (Zandbergen, 2008):

- Errors in the input data - wrongly recorded addresses in, for example, a patient address register.
- Errors in the reference data - wrongly recorded addresses or spatial information in an address database.
- Errors and limitations in the geocoding process - mishandling of input or output addresses limiting the effectiveness of matching, or programming flaws in the geocoding algorithm that lead to incorrect matching (False Positive), or failing to link matching records (False Negative).

Geographic Information Systems (GIS) are useful in address matching as they can both perform geocoding functions, as in the case of ESRI's ArcGIS geocoding extension, and be useful in mapping and analysing the resultant data. However, as noted by Krieger (2003),

simply using a GIS does not ensure success, for instance, it is easy to conflate 'completeness' (the proportion of records in a dataset that have some sort of location attribute attached) with success. Managing to attribute spatial information to all points without considering the quality of that attribution is dangerous: accuracy, and making appropriate choices in how a dataset is geocoded are more important than achieving a 100% completeness (match) rate.

The next sections deal with geocoding a patient register for the London borough of Southwark, firstly specifying the data used, and then discussing in detail the particular methods required to arrive at a final address geocoded dataset.

2.3.4 Using OS AddressLayer 2 for Geocoding

The Ordnance Survey (OS) MasterMap AddressLayer 2 dataset extends the Royal Mail's Postcode Address File (PAF) by adding information on alternative addresses and aliases, as well as classifying known addresses as: straightforward postal addresses, commercial addresses, or subject to multiple occupancy but with only one postal address. The creation and maintenance of Address Layer 2 is important for central and local government functions that require addresses, such as in the Valuation Office, in property gazetteers, for tax purposes and where a citizen-orientated service has to be provided, as it the case in healthcare (but also police, fire, social welfare etc).

As noted by the OS (2009), addresses are dynamic and subject to change for many reasons, including: property (re)development, name changes and fire/flood. The data are under an on-going process of maintenance and revision. The extract used in this research is for December 2009, and covers Southwark, Lambeth and Lewisham, and as such is up to date and spatially extensive enough to include almost all registered addresses of patients receiving primary care in Southwark. The dataset contains 396,507 address records for the area it covers. For the purpose of matching, the AddressPoint data is being used, but this can be linked to OS MasterMap building outline data. The dataset contains the following address data fields:

- Theme - Postal, Non-Postal, Multiple Occupancy
- Flat - Flat name/number (if applicable)
- House - House name/number (if applicable)
- Street - Street name
- Ward - name of ward that record is located within

- Town - town name
- Admin Area - borough/local authority name
- postcode - Full postcode
- Then a set of alternatives: AltFlat; AltHouse; AltNumber; AltStreet; AltStreet2; AltTown; AltPostcode. These denote other possible names or numbers, based upon previous road names, street renumbering, multiple addresses, etc.

The data contain two fields related to position; a value of 'easting' and 'northing' and several that indicate the positional and temporal accuracy of the location. The AGI Address Geography Special Interest Group (AGIAGSIG: 2006) reports on the strengths and weaknesses of OS AddressLayer 2, noting that the OS emphasises data improvements as well as a nationally consistent approach, but finds that it is limited in some important ways. Perhaps the most notable limitations are that the update cycle is quite lengthy, and that there is no specific linkage between the OS and local government. This means that knowledge and address management at a local level is missing, the AGIAGSIG (2006) see this as the most critical weakness of AddressLayer 2.

2.3.5 Address Geocoding Methodology: Standardisation

The Southwark Patient register encodes addresses as in Table 2.1, with two fields for an address and another for a postcode. Of the four columns in Table 2.1, (Padd1-4) only Padd1 and Padd2 seem to be in use; Padd3 and Padd4 are not used in the whole dataset. Generally the addresses are segmented as in Table 2.1, with simpler addresses being recorded in padd2, and more complex addresses being recorded in padd1 and padd2; although this is not universally the case. Crucially, the system does not rely on a full match at all times: addresses can be entered manually if not found in the address register and similarly, partial addresses can be entered (DH, 2010d). Such situations arise if, for example, a building is found, but not a flat within that building.

PatientID	Padd1	Padd2	Padd3	Padd4	Ppostcd
1	[null]	12b St. Percy Road	[null]	[null]	SE1 1AZ
2	Flat 7, Fairfields House	16 Winthrop Street	[null]	[null]	SE16 6TT
...

Table 2.1: Southwark Patient Register address records.

The benefit of the patient register in this form is that for the purposes of address geocoding it is easier to further standardise addresses, some standardisation having already occurred, than it is to start from scratch with free-text addresses.

There are two conceptual approaches to address standardisation: the deterministic and the probabilistic. Recent advances in address standardisation have developed along probabilistic lines using hidden Markov models (Christen and Belacic, 2005; Borkar et al, 2000) or Neural Networks (Bell and Sethi, 2001) to transform free-text addresses into their likely constituent elements. However, in this research a deterministic method is used because the data is already semi-structured and a deterministic procedure is conceptually easier to implement. In general terms, a deterministic approach to address standardisation involves reading in data and performing some kind of computational manipulation of the address string. The standardisation usually occurs prior to the matching process, however in this case the addresses are manipulated throughout the matching process in order to facilitate different kinds of matching techniques. This meant that it was important to be able to structure addresses in different ways throughout the same processes, for this reason an address class was developed in the Python programming language which used a number of methods which could be integrated with a geocoding algorithm. The class follows the schema in Figure 2.7, and was usually implemented in a list object.

Class: Address	
- patID	<i>The unique identifier for the patient record - a long integer</i>
- pAdd1	<i>The first address field from the Southwark patient register, usually flat/apartment - a string</i>
- pAdd2	<i>The second address field, usually a house and street - a string</i>
- pPostcd	<i>The postcode field - string</i>
+ patID()	<i>Returns the Patient ID</i>
+ pcStrip()	<i>Returns postcode field with no whitespace</i>
+ rawCleanSt()	<i>Returns pAdd2 cleaned for punctuation, removing any leading or trailing whitespace</i>
+ stripCleanStreet()	<i>Returns rawCleanSt() but with no whitespaces</i>
+ Street()	<i>Takes rawCleanSt() and returns only the Street element</i>
+ stripStreet()	<i>Returns Street() without any whitespace</i>
+ Number()	<i>Returns the number, or alpha numeric (i.e. 9C), from rawCleanSt()</i>
+ NumberNoAlpha()	<i>Returns the number, but stripped of an alpha-numeric element if one exists</i>
+ rawCleanFlat()	<i>Returns pAdd1 cleaned in the same way as rawCleanSt()</i>
+ stripFlat()	<i>Returns rawCleanFlat() with no whitespace</i>
+ flat()	<i>Takes rawCleanFlat() and returns the flat number or name (i.e. basement flat)</i>
+ flatNoAlpha()	<i>Takes flat() and returns only the numeric part (excludes alphanumeric IDs)</i>
+ house()	<i>Returns the non-flat element of rawCleanFlat(), usually a house or estate.</i>
+ stripHouse()	<i>Returns the house() without whitespace.</i>

Figure 2.7: Class diagram for address in the Southwark Patient Register, 2009.

Computing the return values for methods in the address class involves several functions which interrogate the patient address record for keyword elements. Some of these elements are shown in Table 2.2.

Keyword Search Terms	Synonyms
Flat	Falt; Flt; F
Apartment	App; Apt; Appartment
Other	Room; Rm; Unit; Unt; Suite
Location	Basement; Ground Floor; First Floor; Top Floor
Street	Str; St; Strt
Road	Rd
Other like Road	Alley; Passage; Way; Avenue; Crescent; Drive; Hill; Lane
Estate	Est; Court; House

Table 2.2: A non-exhaustive table of keywords for extracting address data from a string object

There are also some built in functions that return a null value if the data are misleading, for instance if there are insufficient details to break down an address, or if there is too much complexity. This is the case for student halls of residence where the address database may only record a single entry for the hall, but students have been registered to a GP right down to their specific room number, adding several layers of address hierarchy. These cases will go onto to be manually geocoded if possible.

The way in which the data are standardised has a large effect on the overall result; as stated above, bad standardisation can lead to errors in matching, or failure to match records that should be linked. The actual matching algorithm is largely an iterative conditional test that occurs for each record, against all of its possible matches and is described in the next section.

2.3.6 Address Geocoding Methodology: Address Matching

The address matching process, unlike the standardisation process, is a mix of deterministic and probabilistic approaches, using standardisation and deterministic matching when appropriate to speed up the process, and probabilistic 'fuzzy-string' matching when required to account for deviations in the recorded address.

As has been noted previously, the address geography in the UK works largely as a geographic filter. One of the great advantages of the NHSCR data is the robustness of the postcode record, due primarily to its importance in assessing deprivation payments for GPs. The starting point of this address matching algorithm is therefore to create a set of possible addresses based on the patient postcode. This set of potential addresses is tested against

the variously standardised elements of the patient address, the matching process goes through a series of iterations in order to secure a match, from a direct equivalence match (as in Figure 2.3) that first tests the full house number, and then the non-alphanumeric alternative, and then the same process allowing for fuzzy matching of the street. The algorithm continues if the address is a flat, and attempts to match, by the same process, the flat number and, if present, the house or estate details. Any addresses that are not geocoded are tagged as such and can be investigated in a subsequent manual geocoding process. Figure 2.8 demonstrates the logical flow of the address matching process.

2.3.7 Methods for Fuzzy-String Matching in Address Matching

Whilst address standardisation works well in terms of matching the correct addresses, some addresses do not match exactly due to minor typographical errors or abbreviations. In order to accommodate this, fuzzy string matching is used. This allows a match to be achieved if it is within a certain degree of similarity with a record. In the algorithm it is used to match street name and estate name strings. There are a number of methods for comparing and matching fuzzy-strings, ably summarised by Cohen et al (2003). This problem is often referred to as 'the field matching problem' (Monge and Elkan, 1996) and has led to a number of effective algorithms, two were considered in this research; Levenshtein Distance and Soundex. These two were chosen simply because of the ease with which they could be integrated into the geocoding process - Levenshtein Distance is a simple, tidy function that can be integrated into Python, and the Soundex algorithm is implemented in MySQL, the database being used to hold the patient records and the OS Address Layer 2 data.

Process Diagram for Address Geocoding Algorithm

```

graph TD
    Input[Input] --> Success[Success]
    Input --> Failure[Failure]

    RawPatientAddress[/Raw Patient Address  
N = 344,371/] --> Standardise[Standardise]
    Standardise --> PatientAddress[/Patient Address  
N = 343,348/]
    Standardise --> AddressInadequate([Address Inadequate])
    Standardise --> AddressNotMatched([Address Not Matched])
    Standardise --> MatchType4Manual([Match Type 4 - Manual])
    MatchType4Manual --> ManualGeocoding[8) Manual Geocoding - python  
UI, possible address set created  
using soundex on 'street'.  
N = 2,696]
    ManualGeocoding --> AddressMatched([Address Matched])
    ManualGeocoding --> AddressNotMatched

    PatientAddress --> SetPossibleAddresses[/Set of possible  
addresses  
N = 340,236/]
    SetPossibleAddresses --> ConditionalMatch1[2) Conditional match (if var1 ==  
var2 ) for house number and  
street.  
N = 343,348]
    ConditionalMatch1 --> AddressMatched
    ConditionalMatch1 --> AddressNotMatched
    ConditionalMatch1 --> MatchType1Exact([Match Type 1 - Exact])
    ConditionalMatch1 --> MatchType2Fuzzy([Match Type 2 - Fuzzy])
    ConditionalMatch1 --> MatchType3FuzzyAlphanumeric([Match Type 3 -  
Fuzzy alphanumeric])
    MatchType1Exact --> FlatDecision{Flat?}
    MatchType2Fuzzy --> FlatDecision
    MatchType3FuzzyAlphanumeric --> FlatDecision
    FlatDecision --> ConditionalMatch2[5) Conditional match (if var1 ==  
var2) for flat number and estate  
(if available).  
N = 143,147]
    FlatDecision --> FuzzyStringMatch1[6) Fuzzy-string match (if var1  
like var2 ) for flat number and  
estate (if available).  
N = 9,430]
    FlatDecision --> FuzzyStringMatch2[7) Fuzzy-string match (if var1  
like var2 ) for flat number (non-  
like var2 ) for flat number (non-  
alphanumeric) and estate.  
N = 139]
    ConditionalMatch2 --> AddressMatched
    FuzzyStringMatch1 --> AddressMatched
    FuzzyStringMatch2 --> AddressMatched
    ConditionalMatch2 --> NoMatchPostcode([No Match for  
Postcode  
N = 3,112])
    FuzzyStringMatch1 --> NoMatchPostcode
    FuzzyStringMatch2 --> NoMatchPostcode
    NoMatchPostcode --> OSAddress[/OS Address  
Layer 2/]
    OSAddress --> Input
  
```

ing algorithm, represented diagrammatically. N indicates the number of records, arrows suggest success or failure at a given process point

2.3.7.1 Levenshtein Distance

The Levenshtein Distance represents the number of edits (by way of insertion, deletion or substitution of characters) required to turn one string into another (Levenshtein, 1966). Thus, for two name strings calculating the Levenshtein Distance results in an integer value, however this value is meaningless without reference to the length of the string in the first place – 5 edits on a string 5 characters long suggests a completely different string, whereas 5 edits on a string 50 characters long suggests that 90% of the string was the same and that changes were actually minimal. Therefore a ratio is calculated from the number of edits and the length of the strings in question and a floating-point value is returned between 0.0 and 1.0, where 0.0 indicates no string similarity and 1.0 indicates that the strings are the same. This is illustrated in Table 2.3.

String 1	String 2	Levenshtein Distance	Similarity Ratio
Paul Longley	Paul Longley	0	1.00
Paul Longley	Paul Longly	1	0.92
Paul Longley	Pool Longley	2	0.83
Paul Longley	P Longley	3	0.75
Paul Longley	Paul Bromley	4	0.67
Paul Longley	Pablo Mateos	9	0.25
Paul Longley	Michael Goodchild	15	0.12

Table 2.3: Similarity of name pairs using Levenshtein Distance

In the address geocoding algorithm, whenever a street could not be reconciled with any of the possibilities in the set of likely matches derived from a postcode search, there are two possibilities. Firstly, the postcode recorded for the patient may be wrong and the specified street does not link to the given postcode; or secondly that the street may be in the set of possible addresses, however there is an inconsistency between the recorded street name and the street name in the database. In this second case fuzzy-string matching is useful.

The key element of the matching in this case is to match the appropriate street either directly, or by fuzzy matching, and then get the correct house or flat number. Creating a small set of possible streets based upon the patient's postcode means that the number of different street names is limited; trial and error-based experimentation suggested that a limiting value of 0.7 can be used for the fuzzy-string match. Thus, if the two strings return a similarity value of over 0.7 then the strings are considered to be the same. It is unlikely, given the conditions of the possible address set that a similar road will confound the matching.

2.3.7.2 Soundex Algorithm

There are two principal causes of failure in address matching: either the postcode could not be matched initially, so a set of possible addresses could not be created, or a suitable match could not be found in the set of possible addresses. The second circumstance can occur because a given address does not fit the prescribed criteria for standardisation in the algorithm, or because the recorded postcode is wrong. In order to deal with this a semi-automated algorithm is used on the unmatched records after the automated matching process has concluded. The semi-automated process still standardises the addresses and populates a set of possibilities, however the user has to specify the match manually, rather than have the algorithm do it. In this case, the set of possibilities is created by using a soundex-based match on the street name. This returns a set of possible addresses based on a common street where the patient's street 'sounds like' the street name in the address database.

Soundex is a 'phonetic algorithm' that returns a code relating to how a word sounds. It is useful for finding words which sound the same despite variations in spelling. The soundex code for a given word consists of a letter and 3 numbers; the letter is the first letter of the word and the numbers are an encoding of the remaining consonants in the word. Table 2.4 demonstrates how soundex is able to accommodate misspellings in names. It is best used either individually on words, or by removing white space between words. Two strings are compared simply by assessing whether they have the same soundex code.

String 1	Soundex Code	String 2	Soundex Code	Similar?
Paul Longley	P452	Paul Longley	P452	Yes
Paul Longley	P452	Paul Longly	P452	Yes
Paul Longley	P452	Pool Longley	P452	Yes
Paul Longley	P452	P Longley	P452	Yes
Paul Longley	P452	Paul Bromley	P416	No
Paul Longley	P452	Pablo Mateos	P145	No
Paul Longley	P452	Michael Goodchild	M242	No

Table 2.4: Similarity of name pairs using the Soundex Algorithm

Using soundex in this way proved to be an efficient way of deriving a set of possible addresses for manual matching purposes.

2.3.8 Assessing Success in Address Geocoding

The process described above, used for the purpose of address-geocoding patients from a patient register was successful in geocoding 99.2% of the Southwark Patient Register for

2009. However, as noted, completeness is not in itself an indication of success. Certainly, the inflation of the list has been considered, and this may have a confounding effect on results derived from the register; of course it may not be essential to remove these inflated data, as they still reveal patterns about patient behaviour, it is however important that we are aware of such issues in the data and can account for it in an informed way. Further, despite the earlier discussion of place, the process thus far has primarily dealt with 'location', i.e. a patient has been given a more precise position in space, relating to their address. Subsequent analytical chapters will contend that place is created and evidenced by how location is used with respect to the known attributes and behaviours of individuals occupying a particular location. This will be seen to be a partial view of place, but an important one. Firstly, however, it is important to assess the quality of the address geocoding of the Southwark Patient Register.

As noted, the dataset created is 99.2% complete, meaning that of 344,371 patient records, 341,675 were assigned a spatial position. As is evident in Figure 2.8 the geocoding process split these 341,675 patient records into 4 possible types of match (exact, fuzzy, fuzzy alphanumeric, and manual), each indicating a likely level of uncertainty with respect to reality. The match types and break downs are shown in Table 2.5.

Match Type	Count	Count %	Count (Houses)	% Houses	Count (Flats)	% Flats
1	295,789	85.89	152,642	44.32	143,147	41.57
2	12,614	3.66	3,184	0.92	9,430	2.74
3	5,419	1.57	5,280	1.53	139	0.04
4	27,853	8.09	5,324	1.55	22,529	6.54
Unmatched	2,696	0.78	725	0.21	1,971	0.57
Total	344,371	100.00	167,155	48.54	177,216	51.46

Table 2.5: Breakdown of match types by house/flat for address geocoding processes (Match types: 1 = Exact, 2 = Fuzzy, 3 = Fuzzy Alphanumeric, 4 = Manual)

The raw matching data show that the proportion of people living in Flat-type dwellings, which in this case are defined by having a complex address (i.e. an address that cannot be recorded in the patient register in a single column in the form "[house number],[Street name]"), is roughly half of all the registered patients. This is a high proportion of people, which adds complexity to the geocoding, and is reflected by the increased incidence of fuzzy-matching and manual matching for this type of address.

In order to appraise the validity of the address-matching process, samples of the complete dataset were taken and were subject to visual inspection to encode a binary classification of valid match (1) or invalid match (0). These are the effective 'true positive' and 'false positive' measures. It is difficult to assess the corresponding 'negative' measures in address geocoding, as any data that do not match outright is assumed to be 'unmatched' rather than a false negative - if after automatic and then manual geocoding efforts an address could not be matched, it is simply treated as a negative. In any case the interest is in how good the derived dataset is, and so for this we are much more interested in true and false positives than negatives. Conceptually, however, in the patient register all addresses should be attributable to a location, thus any remaining patient records can be viewed as false negatives. To this end the precision (Equation 2.1) and recall (Equation 2.2) functions are estimated from samples (NB. This specification of precision differs from spatial precision discussed earlier). Precision gives an insight into the fraction of the whole dataset that is relevant; the positive predictive value:

$$precision = \frac{\text{number of true positives}}{\text{number of true positives} + \text{false positives}} \quad (2.1)$$

And recall calculates the fraction of the whole dataset that is successfully, and validly, matched; the true positive rate:

$$recall = \frac{\text{number of true positives}}{\text{number of true positives} + \text{false negatives}} \quad (2.2)$$

These two measures subsequently allow the calculation of the F-measure (Equation 2.3), represented by the harmonic mean of precision and recall (Baeza-Yates and Ribeiro_Neto, 2010). It measures the effectiveness, or accuracy, of the matching process. A value approaching 1 is optimal and a value approaching 0 is not. It can be calculated by:

$$F = 2 \frac{precision \cdot recall}{precision + recall} \quad (2.3)$$

The following Table (2.6) summarises values from five samples of 1,000 records in each case, drawn at random from the whole Southwark Patient Register, including unmatched records.

It is clear from the samples taken that the address geocoding process has produced a good quality data set, with few false positives and high levels of precision and recall, and as a result an F score that suggests a high accuracy in the matching process. It is important to note that for the most part false positives arose due to irresolvable mismatches between the

two datasets, particularly where OS Addresslayer2 offered a greater level of detail (i.e. multiple dwellings within an address) that was not reflected in the reported address in the patient register, leading to an arbitrary assignment. Such a false positive will not greatly affect the computation of distance-to-service measures, but may have a larger effect when trying to ascertain a household structure from the data. Some of these issues are targeted in the next section, where the patient register data that possesses a greater resolution than the OS AddressLayer2 can be used to create a slightly finer appreciation of multiple occupancy of dwelling - these are the match results coded 3 (non-alpha-numeric matches) and account for around 5,000 records. The number of people matched to any one specific address identifier is also investigated in order to reveal the presence of larger institutions, or housing that has not been recorded as being sub-divided in the OS AddressLayer2.

Sample #	True positives	False positives	False negatives	Precision	Recall	F
1	981	8	11	0.991	0.989	0.990
2	983	6	11	0.994	0.989	0.991
3	983	3	14	0.997	0.986	0.991
4	983	10	7	0.990	0.993	0.991
5	982	9	9	0.991	0.991	0.991

Table 2.6: Validity measurements for five samples on the geocoded Patient Register

Figure 2.9 shows the frequency of occurrence of occupancy levels of households, derived from the Southwark patient register. Whilst the higher values shall be investigated in order to ascertain whether there are in fact large numbers of people per household, or whether the data will allow further subdivision in some cases, what is apparent is a very strong exponential distribution (linearised in the inset to Figure 2.9). This exponential distribution is a very interesting characteristic of how people live; single person households are most common, two person households are next and so on, but in a way where the decay is exponential. This is most likely a pattern caused by a combination of existing housing stock and individual choice.

The presence of the long tail in the data is interesting. It shows that there are multiple occurrences of large numbers of people per household. This could be due to limitations in the data which could affect the intuitive validity of the process, therefore households with large numbers of people apparently residing in them are explored for explanations as to why this might be the case. A

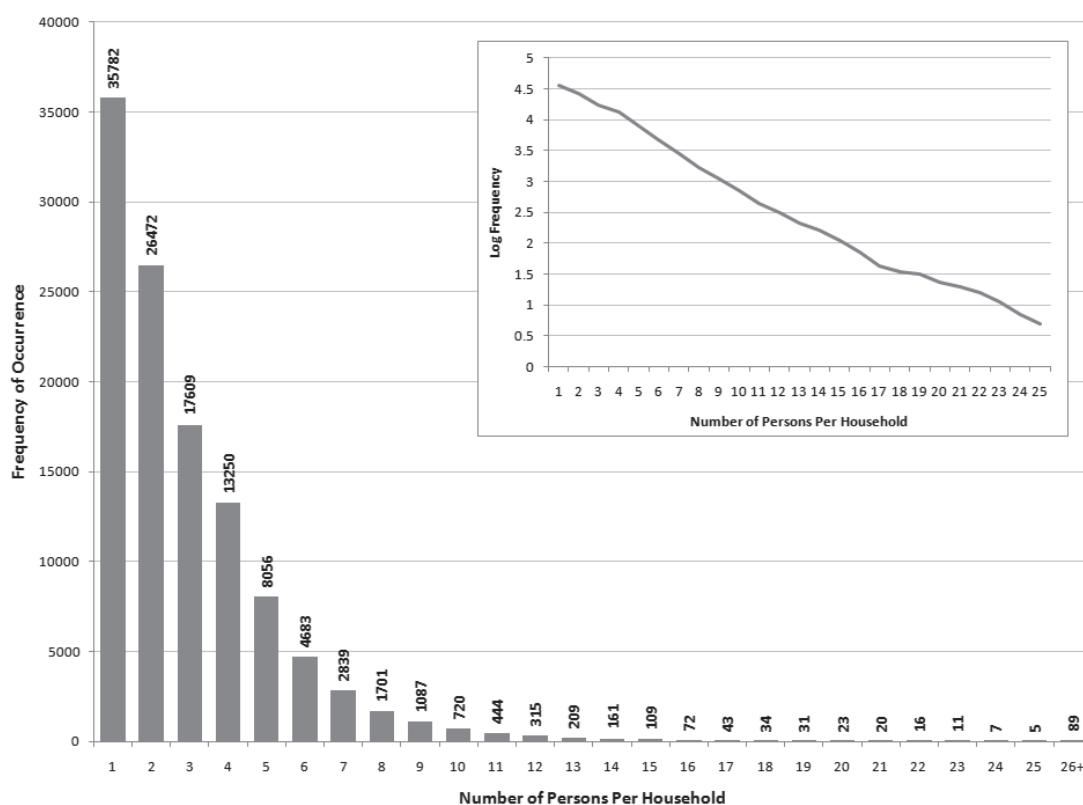


Figure 2.9: Frequency of occurrence of household size, with log-plot inset

primary example of this are the nine dwellings for which there are 1091, 1057, 497, 337, 279, 279, 231, 139 and 177 persons associated respectively, closer inspection reveals they are blocks of housing in which AddressLayer2 only records a single building rather than the many subdivisions present. In these cases the patient register holds no more detail, although an online search reveals that the buildings in question are university halls of residence.

The largest entry for a single dwelling that is not a University hall of residence is a dwelling with 146 persons matched with it. Closer investigation reveals that it is a centre for accommodating refugees. Likewise, a dwelling with 141 persons associated with it seems to be a hostel, documenting the transience of particular populations in Southwark. Further, a dwelling with 111 persons associated is an elderly care home. In fact in this long tail, larger institutions such as those listed above account for the largest 47 dwellings and around 6,500 people, there is no additional information attached to them beyond an address identifying the institution, so they remain as large groupings of people who are transient (i.e. travellers, asylum seekers/refugees, students) or vulnerable (elderly and/or infirm) populations.

Investigating the matches that dropped the alphanumeric component of the address (i.e. using 9 rather than 9C if no 9C match was available in OS AddressLayer 2) coded as match type 3, allows the addition of 1561 households derived from the patient register. These all

retain the specific location encoded via OS AddressLayer2, but add some additional reporting in terms of specifying multiple occupancies that were not previously reported. Of course, the Figure of 1561 only accounts for 1.4% of the total derived addresses owing to the pre-existing richness of OS AddressLayer2. Many of the addresses coded as 3 and subsequently interrogated to add additional richness relate to subdivision of houses, rather than issues recording apartments and blocks of social housing. Ostensibly, data integrated into OS Addresslayer2 from Royal Mail sources has a tendency to acknowledge houses in multiple occupancy but only 1 delivery point (i.e. a house with multiple flats, but a single letter box) as a single record - this is useful for effective delivery of post, but problematic when assigning individuals to a specific household as in social research.

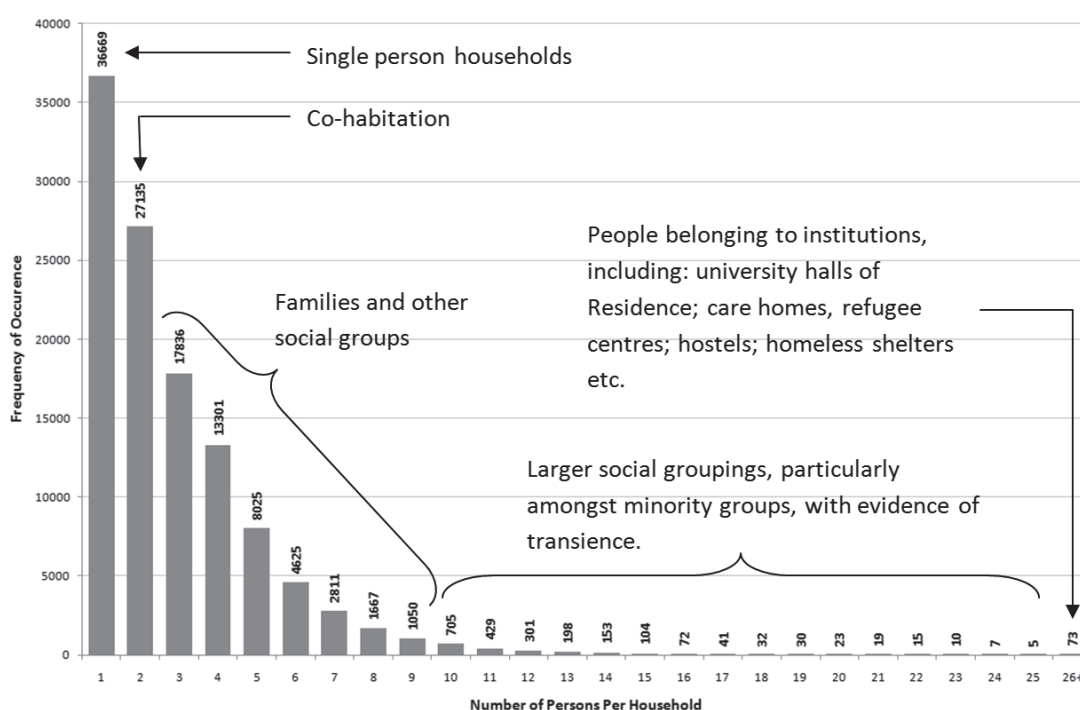


Figure 2.10: Frequency of Occurrence of Household Occupancy, revised with explanations.

These actions leave us with the picture shown in Figure 2.10. As it stands the data does not afford us any further level of discrimination. An investigation of date of registration with respect to houses with high levels of registration may reveal patterns of short-term occupancies, however the cleaning of out-dated registrations takes place too sporadically and over too great a time frame for this to be conducted in an empirically robust fashion.

Having successfully address geocoded the Southwark patient register, and extracted both the building-level and household-level groupings of individuals, a further attempt can be made to characterise those households in terms of their life-stage as detailed next.

2.3.9 Lifestage and Geodemographic Classification

Lifestage and geodemographic classifications are primarily used in marketing and demography in order to reduce the complexity of the multidimensional data linked to households or small geographic areas (Harris et al, 2005). By segmenting the numerous combinations of household compositions, or population behaviours within areas, into a smaller set of similar classes, an understanding can be gained of the general set of needs and behaviours specific to each group. Webber (2004) suggests that “Government is increasingly using such methods to improve the targeting of its own communications to tailor local service delivery to the particular needs of local communities” (p.1). Appending a household life stage classification to existing patient register data, in which address geocoding has derived households, can reveal new trends, and previously hidden aspects, in patterns of service registration and residential ordering. Likewise information about the neighbourhood, or small area, within which a patient lives allows the development of an understanding of social context and aggregate behaviour of patients and households. Both offer a previously unavailable insight into patterns of patient behaviour that could be of great benefit to commissioning health services.

Previous work within the context of geography developed from marketing and commercial applications, Beaumont and Inglis (1989) exemplify this with a focus on retail, and the economic advantages to be gained through segmenting households. Others innovated the creation of ‘geodemographics’ from the sociologists Shevky and Bell’s (1972) work on “social area analysis”, although Charles Booth’s poverty maps from the very end of the 1800s are often cited as landmarks in household classification (Harris et al, 2005). Commercial geodemographic systems have proliferated in recent years, and the development of the ONS’s (Office for National Statistics) own free and open-source geodemographic classification based on the 2001 Census aggregate statistics, known as the Output Area Classification (OAC), represents an acknowledgement by Government as to the power of market segmentation-style classification for understanding society. This is manifest in recent movements within government sectors toward “social marketing”. Kotler and Zaltman (1971) underline the potential of social marketing, stating that “the art of selling cigarettes, soap or steel may have some bearing on the art of selling social causes” (p. 3). The uptake of the term “social marketing” alongside geodemographic classification has only come about recently however; public health has been a key contributor to the development of social

marketing (cf. DH, 2008a), moving from Kotler and Zaltman's early definition that social marketing covered "the design, implementation, and control of programs calculated to influence the acceptability of social ideas and involving considerations of... marketing research" (1971 p. 4), to a contemporary understanding developed by Andreasen (1994) in which "to be labelled social marketing, a program must: apply commercial technology, have as its bottom line the influencing of voluntary behaviour, and primarily seek to benefit individuals/families or the broader society" (p. 112). The NHS's "Choosing Health: making healthy choices easier" (DH, 2004) was a watershed for health promotion agendas, and actively supported the use of commercial marketing techniques in fighting health inequalities and enabling people to make healthier lifestyle choices. This agenda looks set to continue in the reformed NHS, and is further supported by the increased marketisation of primary care services, and broadening of patient choice initiatives (DH, 2010b).

2.3.9.1 Appending ACORN to the Southwark Patient Register

ACORN (A Classification Of Residential Neighbourhoods) is a commercial geodemographic classification of the UK population based on demographic, behavioural and attitudinal variables (CACI, 2009). It is aggregated at the postcode level, creating a 3-level nested hierarchy, with 5 top level groups, 17 mid-level groups and 56 groups providing a fine grain perspective at the lowest level. CACI claims that the classification contains over 225 demographic statistics and 287 lifestyle (behavioural and attitudinal) statistics. Unlike OAC, as ACORN is a commercial classification the detailed methods, data sources and weights underlying its construction are undocumented (OAC is fully documented: see Vickers and Rees, 2007). However a consideration of the two classifications in Southwark revealed that OAC was not as effective a spatial discriminator as ACORN. The OAC classification essentially created a duality with much of Southwark classified into 1 of 2 main groups, which did not reflect the diversity of neighbourhoods in Southwark as well as ACORN did. ACORN also offered a finer spatial scale (postcode vs. OA) which potentially lessened the effect of the ecological fallacy (MAUP: Openshaw, 1984). Whilst this may be partially in evidence for Southwark, Singleton (2007) suggests that on a national level there is little to be gained from the spatial scale of a geodemographic classification dropping from OA to postcode.

It is straightforward to append the ACORN classification to the Southwark patient register data, and either of 2 ways can be exercised. The classification can either be appended directly to the data table, joining the patient postcode reference with the appropriate

postcode recorded in the ACORN classification data table; or the ACORN classification can be joined to the appropriate areal postcode geography, and a spatial join enacted to the patient register data, represented as easting and northing coordinate pairs, within a GIS. Having achieved this, every individual and every household has a contextual variable attached relating to the aggregate lifestyle characteristics of people living in their neighbourhood.

2.3.9.2 Deriving a Household Lifestage Classification from the Southwark Patient Register

Classifying the lifestage of a household simply means to characterise each household in question as belonging to one of several prescribed classes related to where the inhabitants of that household are in their lifecourse – does the household represent a young family, an elderly couple or a single man? In market research it has been shown that different purchasing behaviours can be associated with households at different stages in their life cycle. Classifying households in the Southwark patient register allows consideration of whether patterns of registration exist by household type.

Class	Household Reference Person Age	Composition
1	16 - 24	No dependent children
2	16 - 24	With dependent children
3	25 - 34	No dependent children
4	25 - 34	With children aged 0 – 4
5	25 - 34	Youngest child aged 5 – 10
6	25 - 34	Youngest child aged 10 – 15
7	35 - 54	No dependent children
8	35 - 54	With children aged 0 – 4
9	35 - 54	Youngest child aged 5 – 10
10	35 - 54	Youngest child aged 10 – 15
11	55 - 74	Single Person Household
12	55 - 74	2 + persons, no dependent children
13	55 - 74	With dependent children
14	75 +	Single person household
15	75 +	2 + person household

Table 2.7: Household lifestage classification

Whilst Figure 2.10 presents an informed speculation on the characteristics of households as they differ by household size, a more rigorous approach can yield a useful segmentation of households based on available data pertaining to household size, age and sex. There is no industry standard household lifestage classification (Leventhal, 2010), however more detailed data about households will allow for a better targeting and profiling for social marketing,

and market research applications, as well as having benefits to the creation of neighbourhood geodemographics. In this thesis a classification created by the Market Research Society's Census and Demographics User Group and proposed for inclusion in the Census 2011 is used. Table 2.7 shows the specifics of this classification.

The chosen classification is ideal because it can be constructed with the limited demographic information available in the Southwark patient register. Having geocoded individual patients to a position in geographic space based on the patient's reported address, patients can be grouped into households by adding an identifier when individuals all have the same address. This means that not only can individuals sharing the same building be identified through the sharing of the same easting and northing, but within that shared geographic space households are defined by address differences such as the flat number. For each of these households it is simple to interrogate the members and detect the ages of any adults and children and position the household within the classification given in Table 2.7. The resultant distribution of households in Southwark is shown in Figure 2.11.

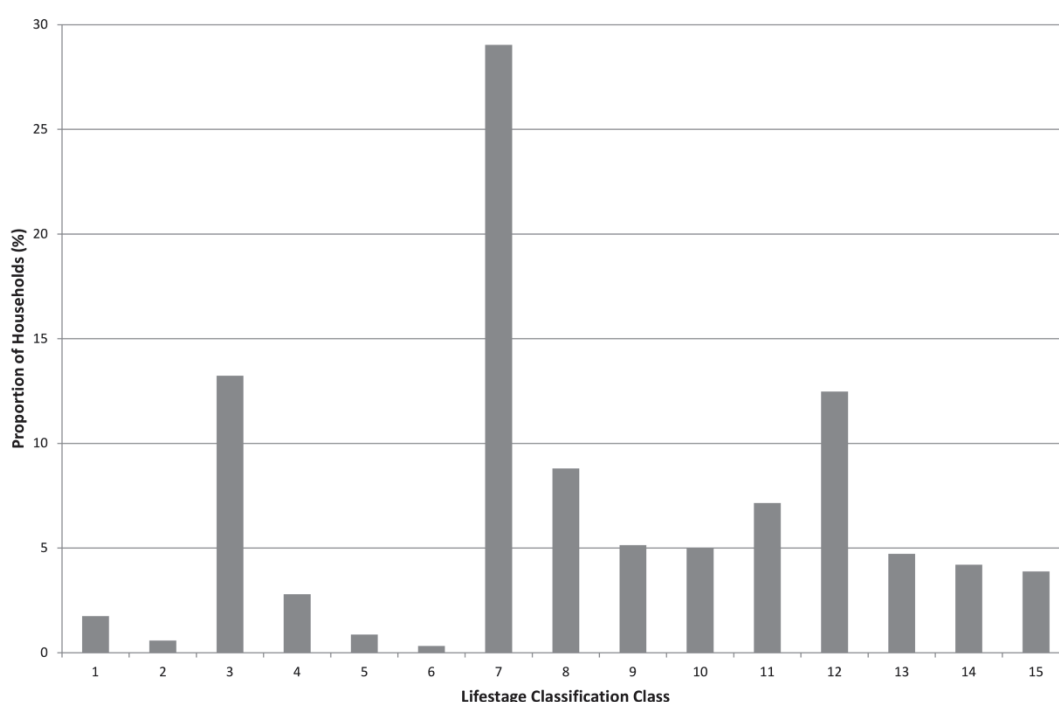


Figure 2.11: Distribution of households in Southwark patient register across lifestage

There are some confounding aspects to consider in this process however, the most significant being the selection of a household reference person (HRP), who is intended to characterise the household as a single entity (Martin and Barton, 1995). Traditionally, when household surveys were undertaking the HRP was defined as the oldest male member of the

household. However, contemporary surveys are conducted on the basis of the HRP being the person who owns, rents, or is otherwise responsible for the accommodation. Martin and Barton (1995) suggest that this is a more appropriate basis for characterising households, they also advocate that in the event of a tie (two or more householders responsible for accommodation) the highest earning householder be the HRP. They state this on the basis that in selecting between a couple, age is often a fairly arbitrary divider. The key change is to acknowledge the increasing importance of women in the household, and indeed the steady dissolution of the household as synonymous with traditional family structures. As there is no information within the Southwark patient register as to household income, or who is responsible for the accommodation the only recourse is to simply select the oldest adult as the HRP. However, a caveat arises out of the complexity of some households, in situations where there are elderly household members (assumed here to be 65 for a man or woman) living with other younger adults, the HRP is assumed to be the oldest non-elderly household member.

An attempt is made to classify all households, including those that are very large (0.1% > 20 persons, 1.3% > 10 persons, 6.7% > 6 persons, of defined households) and possibly represent institutions. If the analysis requires, these large households, which may demonstrate behaviour that is unrepresentative of the broader set of residential households, can be filtered out by selecting only households below a certain size. Furthermore, their overall impact is likely to be low anyway as they represent a tiny minority of the observed households in Figure 2.11. In some cases (0.5% of defined households) a child is found living alone in a household. These households are marked as unclassified as they most likely represent a situation in which the parent(s) or guardian of the child is not registered with a GP surgery, and hence does not appear in the Southwark Patient Register, or the household is outside of Southwark and the parents are not registered with a Southwark GP surgery although the child is.

This method of classification is experimental, and it demonstrates the potential to augment existing data in order to develop new explanatory variables. However this is not what the data were primarily intended for and should be treated with appropriate caution. It is very difficult to assess the validity of this classification: we know that the patient register upon which it is based may be subject to some degree of inflation, however on an individual level we rationalise the inclusion of all data on the basis that they still potentially says something

interesting about patterns of registration. As has been noted, it is impossible in the context of the data set to remove any patients on any basis other than assumption, thus there is scope for the misclassification of individuals into households, and this in principle will bias the household lifecycle classification to an unknown degree. Therefore, conclusions drawn from the classification should be interpreted with care.

2.3.10 Classifying Patient Ethnicity using Onomap

There is no coding of patient ethnicity within the Southwark patient register, a situation true of all NHSCR records. Senior and Bhopal (1994) suggest that ethnicity is increasingly important to health and epidemiological analyses, but that it is not a straightforward concept implying one or more of the following conditions: “shared origins or social background; shared culture and traditions that are distinctive, maintained between generations, and lead to a sense of identity and group; and a common language or religious tradition” (p. 1). The closest thing that exists in the raw data is a field that captures place of birth. However, place of birth fails to capture ethnicity as well as excluding second generation immigrants who were born in the UK. The place of birth field is also somewhat difficult to interpret, as on the NHS GP registration document it is a free-text field in which patients should write:

- Place of Birth, and County, if born in the UK
- Country of Birth, and date of arrival in the UK if born outside the UK

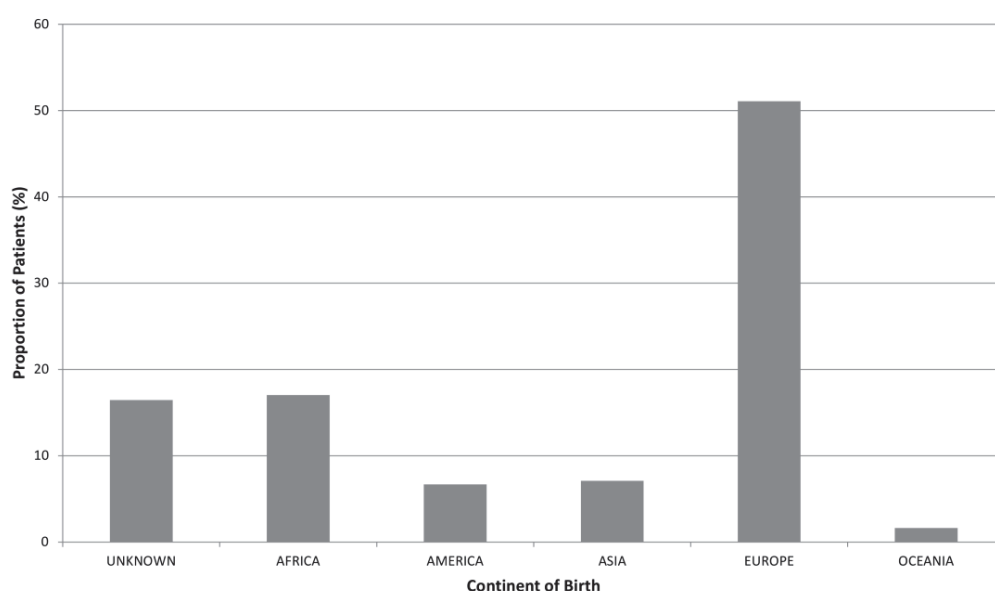


Figure 2.12: Place of birth by continent for Southwark Patient Register

In 16% of cases, there is no record of place of birth, equating to around 1 in 6 patients.

Those that remain offer a variegated understanding of place of birth, with entries including:

home birth; the hospital of birth; and varying levels of precision for those born outside of the UK. One of the largest issues is dealing with the numerous ways in which places of birth are (mis)spelt. In order to derive something useful from this complex free text field the patient register is run through the “birthplace geocoder”, a piece of software which cleans and standardises the place of birth field (Mateos, 2005). It is also possible to capture the arrival date of patients, but this data is very partial with regard to immigrants and is not captured in this instance. Figure 2.12 documents place of birth by continent for individuals in the Southwark Patient Register.

In order to tackle the size of the unknown group, and investigate the presence of 2nd generation immigrants, the Onomap classification can be employed. Onomap is a classification of a person’s cultural, ethnic or linguistic origin based upon their forename and surname. Mateos (2007; Mateos, Webber and Longley 2007; Mateos, O’Sullivan and Longley, 2011; Lakha et al, 2011) demonstrates that different forenames and surnames, and different combinations of forename and surnames, are specific to particular languages, countries, regions, religious affiliations, cultural groups or ethnicities. Onomap is able to make a reasonable assessment of ethnicity by understanding the implications of the name of a given patient, with a granularity that far surpasses the UK 2001 Census. Onomap has 185 categories based on a hierarchical structure of sixty-six Onomap subgroups and sixteen groups, whereas the census records only 16 possible ethnicities. There are some limitations to the Onomap classification, primarily based on its reliance on a forename-surname style of naming, which may differ in some cultures, particularly non-western ones. Similarly, classification that involves an individual’s surname will bias the assigned ethnicity to that of the father, since most surnames are defined by patrilineage, i.e. the taking of the family name from the male line. This may hide ethnicity in cases where the mother has a different ethnicity and the offspring identifies more with the matriarchal ethnicity. Finally, because the classification relies on names alone it is susceptible to the use of non-ethnic names by populations for historic reasons, for instance due to the effects of colonialism and slavery through plantation ownership, there is a tendency for the peoples of the West-Indies and Caribbean, in some cases, to use ethnically English names, meaning that the Onomap classification will mistakenly identify them as ethnically English rather than Afro-Caribbean.

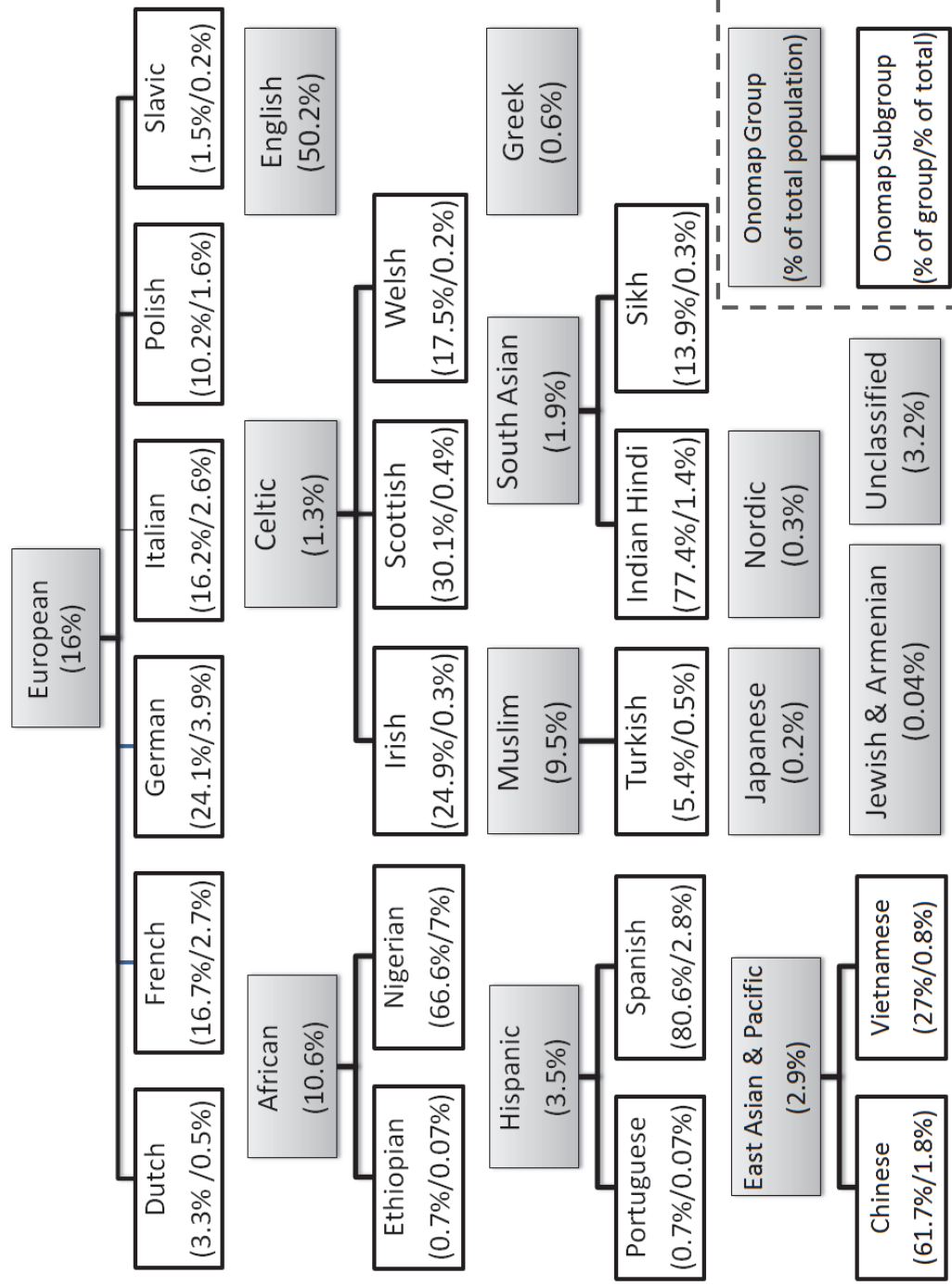


Figure 2.13: Ethnic composition of Southwark Patient Register by Onomap group and sub-group hierarchies

An attempt to mitigate this is undertaken using the cleaned place of birth data recoded as a binary variable to show nationals (UK-born persons) and immigrants. This binary variable can be cross tabulated with Onomap ethnicity to understand where second generation immigrants might exist.

The process of coding patients using Onomap gives a rich insight into the ethnicity of patients. Figure 2.13 describes the major ethnic, cultural and linguistic groupings in the Southwark patient register. There is a huge amount of flexibility available to then recode the Onomap classification into a set of useful and representative groups for Southwark. Table 2.8 demonstrates the classification that is used in this thesis for analysis concerning the Southwark patient register. The groups defined in Table 2.8 represent a fairly broad cross-section of Southwark groups, their inclusion motivated by several factors: primarily, that groups should have sufficient numbers in order to conduct robust statistical analyses, but also in order to reflect recent migrations (such as Eastern European groups). In other cases it was not possible to dissolve groups any further: the African population is predominantly Nigerian, and the rest of the group is either classified into very small classes representing other African countries or a large generic African group. The Hispanic group remains separate as Latin American names cannot be disambiguated from it, and the Hispanic group seems to behave differently to the other European groups as will be evident in subsequent chapters. The unclassified and other group now only accounts for 4% of all patients, unlike the 16% in the place of birth field.

Ethnic Group	Example Constituents	% of Patients
African	Nigerian, Ethiopia, Ghanaian, other African	11
British and Irish	English and Celtic (Irish, Welsh, Scottish)	51
East Asian	Chinese, Vietnamese, Pacific Islands	3
Eastern European	Ukrainian, Slavic, Serbian, Russian, Polish, Romanian, Latvian, Lithuanian, Hungarian, Albanian. Estonian, Bulgarian, Greek	2
Western European	French, German, Italian, Belgium, Netherlands, Nordic, Swiss, Austrian	13
Hispanic	Spanish, Portuguese	4
Muslim	Turkish, Middle East, North African, Pakistani	10
South Asian	North Indian, Hindi, Sikh	2
Other	Japanese, Jewish and Armenian, Unclassified	4

Table 2.8: Onomap Classification used for Southwark Patient Register.

If we cross-tabulate the Onomap classification of the Southwark data with the binary indicator of immigration derived from the place of birth field, the proportion of each group

that was born in the UK or Ireland (grouped as it is difficult to distinguish Irish from other Celtic peoples in Onomap), then it is possible to get an insight into the uncertainty inherent in the Onomap classification. Table 2.9 presents an interesting picture of the number of second generation immigrants in the various non-British and Irish groupings: around 25% of all Africans in Southwark were born in the UK or Ireland, and likewise around 30% for Muslims and South Asians.

Onomap Group	Born in UK or Ireland (%)	Born outside UK/Ireland (%)	Unclassified (%)
African	26 (2.8)	68 (7.2)	6 (0.6)
British and Irish	58 (29.8)	20 (10.3)	22 (11.3)
East Asian	16 (0.5)	74 (2.1)	10 (0.3)
E. European	16 (0.4)	79 (1.7)	5 (0.1)
W. European	30 (4.2)	57 (8.0)	13 (1.9)
Hispanic	16 (0.5)	78 (2.7)	6 (0.2)
Muslim	30 (2.9)	59 (5.6)	11 (1.0)
South Asian	31 (0.6)	57 (1.1)	12 (0.2)
Other	24 (0.9)	68 (2.7)	8 (0.3)

Table 2.9: Cross-tabulation of Onomap Groups with place of birth. xx = % of group, (xx) = % of population

One area for concern with respect to Table 2.9 however, is the large proportion (20%) of people classified as British and Irish being born outside of the UK or Ireland. Breaking down this group it is evident that this statistic is a direct result of colonialism on many fronts (Table 2.10). There is little of practical value that can be done with regard to the apparent cross-classification of British and Irish names. Whilst the American and Oceanic groups might be thought of a culturally similar, the Asiatic and African cross classification is of greater concern, however as a proportion of the overall population the potential for sizable effects due to this possible error are low. In this vein, the Western Europeans shown as born in the UK or Ireland in Table 2.9 may partially reflect the similarity of some names across Europe.

Continent of Birth	% of British and Irish Group	% of Population
Africa	38	4.0
America	33	3.4
Asia	7	0.7
Europe	9	0.9
Oceania	13	1.3

Table 2.10: Continent of Birth for patients with British and Irish names born outside of the UK or Ireland.

The other cause for concern is the relative variation in unknown places of birth across the different Onomap ethnicities. Given that the percentage of unknowns is lower for recent

migrant groups (i.e. Eastern Europeans, and Hispanics) and higher amongst more traditional migrants (i.e. South Asians and Muslims) this may simply reflect the temporal differences in data collection on the part of the NHS. The British and Irish group has the largest number of missing places of birth, which may reflect a systematic lack of adequate collection of that variable in the past that has been superseded by a growing need to understand the diversity of patients using healthcare services. This is certainly in evidence in the attempt to record arrival dates of immigrants in the place of birth field as well.

The use of the Onomap classification is naturally limited, however without another good indicator of patient ethnicity it is by far the best possible representation of ethnicity available. It is used for this reason, and subject to the limitations discussed.

2.3.11 Consolidation: Southwark patient Register

This extensive section dealing with the Southwark patient register has introduced the dataset, acknowledging the nuances and limitations to its use, whilst also highlighting the privilege that exists for a researcher in being able to access and use the data at such a fine scale, subject to the appropriate ethical approval mechanisms.

In examining the data, several aspects of its augmentation are examined in detail. Firstly, the process of geocoding the data at the address level is discussed; secondly, the application of a household lifestage classification; and thirdly the coding of patient ethnicity using Onomap. The dataset in this form is the dataset that is referred to as the Southwark patient register in the following chapters. The next section deals with the other key dataset in this thesis, Hospital Episode Statistics (HES) data.

2.4 Hospital Episode Statistics

2.4.1 Introduction to HES

“Hospital Episode Statistics” is an umbrella term that describes England’s data warehouse for statistics relating to care provided by NHS hospitals (NHSIC, 2011). Like many NHS information technology functions access to the warehouse itself is hosted by a private company on contract to the NHS. It includes private patients who were treated in NHS hospitals, and patients resident outside of England (Welsh patients are coded geographically, whereas Scottish and other patients are not). The HES contain data for both

inpatient (overnight stays in hospital) as well as outpatient appointments (care that cannot be provided by GPs at a local surgery). Recently the NHS has experimentally release Accident and Emergency data, but these are not considered in this thesis. The HES essentially contain a record (episode) for each hospital admission (inpatient) or attendance (outpatient) in England.

HES data came into being as a result of the Körner Report (1982) which sought to amend a lack of statistical data available to support healthcare planning. The core message was that much of the required data could simply be lifted from existing records taken as a matter of course in providing care, if only the appropriate structure were in place to do so. This has now become a common approach to data in the NHS, and, as discussed earlier, primary care data are beginning to be gathered together in this way. At the time of the Körner Report, hospitals were very much the focus of the NHS (Moon and North, 2000) and hence this took precedence in terms of strategy and data collection. Hospitals are also somewhat less numerous than primary care medical centres and arguably represented a more centralised resource, making complete data collection, if not easier, certainly more attainable.

Presently, tabulated reports can be generated directly from the NHS information centre's "Hesonline" website: however, the available data are aggregate and only available at large areal levels related to primary care or hospital trusts. The research presented in this thesis deals with preference expressed at small area levels and requires an extract of data to be acquired in order to fulfil this intent. Such data requests come at a price, in terms of the time taken to compile an extract and gain any required ethical approval, as well as a monetary expense for the compilation itself. In obtaining extract data in this way, a license is entered into with the NHS pertaining to security as previously documented.

There are numerous inconsistencies in HES data associated with changing data collection practices over time (such as the move from ICD 9 to ICD 10 as a standard for recording diagnoses), and with organisational changes to the NHS (such as shifts in NHS fundholding). Whilst HES data have been recorded in its full form since 1989, this research uses data from 2003 onwards as it represents a time in which NHS trusts and PCTs were in place, and ICD 10 had been adopted as the standard for recording diagnoses. There were some shifts during this time, such as the reduction in number of Primary Care Trusts in 2006, however

this should be manageable compared to dealing with large systemic changes. It is important to acknowledge that the inpatient data are of better quality than the outpatient data, largely because it is mandatory to capture the data for inpatients, and patients are essentially captive (at least overnight), whereas outpatient attendances do not strictly require the same rigour of data capture (although in principle these data are collected) and the comparative transience of attendance by patients may make the data more difficult to compile.

2.4.2 HES data used in this thesis

There is a huge amount of data stored in HES, and the overriding concern in this thesis is to identify and extract those fields that are appropriate to the particular research question being asked. As this research pertains to behaviour and patterns of usage of hospital services in general, the following field types are extracted:

- Patient demographics: patient age, sex and ethnicity
- Arrival: how did the patient get to the hospital?
- Primary diagnosis: what was wrong with the patient?
- Patient location: where does the patient live? Coded in terms of Lower Super Output Areas (LSOA), a government census dissemination areal unit of c.1500 people.
- Referring GP code: If referred, a code referencing the referring GP surgery
- Hospital trust: a code relating to the hospital trust providing care.
- Outcome: Whether or not the patient survived.

An extract was created for the years 03/04 to 08/09 inclusive. Over this period the number of records (each of which denotes a single hospital episode) increased from 14.1 million and 51.4 million for inpatients and outpatients respectively in 2003/04 to 17.4 million and 74.9 million by 2008/09. These huge datasets require a large amount of storage – over 40 gigabytes for HES and its associated data tables – and can take a long time to query, and thus requires a powerful computer and effective data handling efforts.

In addition to the HES, a number of extra data sources are required to provide context. To start with both inpatient and outpatient datasets have an extensive data dictionary which is crucial to interpreting the coded responses within the data. Secondly, two lookup tables are required to locate GP surgeries, and NHS trust providers. The locations of GP surgeries are derived from a register available through Neighbourhood Statistics, which locates GP surgeries, for the most part (around 90%), at the address level, and those that it cannot, at

the postcode level. The same is not directly true of NHS trusts, however Connecting for Health (CfH) keeps a flat file of all hospital trusts, codes and addresses. This can be geocoded to postcode and integrated into the database. Finally, a series of geographical lookup tables are required to link the patient locations to geography: HES encodes patients to LSOA (Lower Super Output Area) in the Neighbourhood Statistics Service (NeSS) hierarchy (NeSS, 2010), which means data can be aggregated to Middle Layer Super Output Areas (MSOAs) of around 7,500 people, or to Local Authority districts, counties, GORs or nationally. The LSOA-level coding of patient residence locations means that the ONS Census Geodemographic classification for LSOAs can be applied if required, this is similar in principle to OAC, but provided at a higher level of aggregation.

In addition to the geographically based lookup tables, an aggregation of the ICD 10 is also employed in order to reduce the complexity and specificity of the primary diagnosis field. Whilst ICD 10 may be useful for in-depth epidemiological studies, it is more appropriate to generalise it for consideration in investigations with wider scope, such as referral patterns. To this end, CCS ICD-10 is employed, which is a lookup developed for the express purpose of collapsing the huge number of ICD 10 diagnosis codes (more than 32,000 in total) into a small number of “clinically meaningful” classes deemed particularly useful for descriptive statistics (Elixhauser et al, 2011).

2.4.3 Consolidation: HES data

The core consideration to using HES data is that they are managed in an appropriate way, conducive to ease of analysis; MySQL is an effective tool for this, although due to the sheer amount of data it can still suffer from long computation times on some queries, particularly when joining data across several tables. In addition, the use of an RDBMS facilitates data security as required by the HES extract. Whilst complete data outputs can be achieved wholly with the database, any mapping and spatial analysis of results is conducted outside, in GIS software or by scripting the desired procedures in a programming language.

The dataset in this form, and subject to the appropriate addition of spatial and contextual data, is referred to as HES data henceforth in this thesis.

2.5 Consolidation: Spatial Data Infrastructure for Healthcare Planning

This is a chapter in two distinct parts: firstly it engages with the underlying issues that abound in the NHS with regard to managing and utilising available health data, with particular reference to spatial or geographic information; and secondly, it describes the data used in this thesis with particular reference to the ways in which the data sources are manipulated in order to augment their usage, and make them fit for purpose.

Clearly, some sectors of the NHS are better equipped with regard to available, operational data than others. HES is a vastly more mature dataset than the Southwark patient register data and as a result of this it requires considerably less manipulation and attention in order to develop workable and useful variables out of it. At the same time, as the data are, in a sense, much more widely understood, there is comparatively less opportunity to develop new insights spatially through manipulating the data. One of the key benefits of HES relative to the patient register data is the size of the community of users that surrounds HES, and the documentation that accompanies it. Indeed, the legacy of HES means that it is possible to get a national extract of the data at as low as postcode level (subject to ethical approval), whereas the primary care registration data would be somewhat harder to acquire either from individual PCTs, or from PCT clusters, creating an large data collection overhead if the desire was to do any kind of larger regional or national-level analysis of registration. Having said this, the Southwark patient register is a manifestation of the detailed data collection practices of the primary care sector, and the usage of the patient register allows a hitherto unseen level of spatial resolution into patterns of registration with general practice doctors' surgeries.

It is clear that the NHS is still some way away from implementing the kind of spatial data infrastructure that would make the data gathering aspect of spatial research straightforward. There is an effective data infrastructure in place to serve HES data, however it fails to integrate the spatial data required to look more deeply at referral flows of patients. That the patient data is referenced to NeSS geography, is compatible with the UK Census of Population and a larger raft of contextual and compositional information, and is useful for integrating spatial information, means that it can be seen as a stepping stone towards a formal spatial data infrastructure. Primary care data is a less certain proposition. One system

known as QMAS (Quality Management and Analysis System), which facilitates the collection of evidence pertinent to the quality of care that GPs are providing: however these data are primarily administrative, accounting for how GPs are paid through the QoF (Quality and Outcomes Framework) aspect of the GP contract (DH, 2009b). As such QMAS is not suggested for use as a data source for assessing GP surgery quality, as the NHS claims its remit for collection is too partial for this, similarly with GPs striving to earn as much as possible, there is in effect little scope for distinguishing between the majority of GP surgeries. The possibility of primary care data on usage is something that would help to dramatically improve the operation of primary care, and would be particularly important to streamlining the primary care efforts of the NHS at a time of great importance for the effective operation of primary care. However, as noted, centralised efforts to affect this have failed and been cut from the government budget as a result of public spending restraint, whereas new proposals with regard to joining up data are merely under consultation. It cannot be expected that each PCT (or each GP consortium as they seem set to become) can oversee the commissioning of primary care by employing a spatial analyst to query the effectiveness of the local network of care provision – this simply is not efficient. Fundamentally, the NHS strongly requires a spatial data infrastructure in order to take hold of public health with respect to primary care, or else local communities will find themselves under- or ineffectively provisioned in the short and medium term, and the gradient in neighbourhood health identified by the Marmot review (2010) will only increase.

In the next chapter, consideration is given to the geographic representation of the data sources that has been outlined here. Subsequently, demographic and health insights are investigated as a result of using the data for descriptive purposes. This demonstrates the effectiveness of using the datasets for demographic, as well as healthcare planning purposes, widening the remit and potential audience for such key spatial datasets.

3 Representing Healthcare Information

3.1 Introduction

A core function of a GIS is the ability to assemble geographic information, and represent it in ways that can be used to derive and communicate new knowledge and understandings of spatially distributed phenomena. According to Longley et al (2011), GIS-based representation entails the digital encoding of some element of the natural or social environment, such that it can be understood in a consistent and useful way. The usefulness of representation stems from the potential to discard unessential detail about the world while retaining salient elements that may be transformed, queried and analysed at will. This allows us to experiment with the world, and test hypotheses as to why the world works in the way that it does – issues that are often obscured can be interrogated freely within a computer environment. The oft-called “father of GIS”, Roger Tomlinson, saw GIS as a policy decision support system (Tomlinson, 1974), and on this basis representation becomes crucial to the direction of effective policy and government interventions.

Specific consideration is required when it comes to thinking about the representation of information pertaining to geographies of health. In the context of this thesis there are several important facets to representation to consider. First, and most practically, what are the representational options available for viewing the kind of health data discussed in Chapter 2? Second, how do different representations alter the conclusions or associations that it is possible to draw? Third, and more conceptually, how do these representations fit in with contemporary understandings of space and place in health and medical geography?

In seeking explanations to these questions, the chapter first begins by considering further what representation entails in Geography, GIS and Health and Medical Geography.

Subsequently, the kind of representations that are dealt with in this thesis are explored, and some descriptive examples that emerge from the datasets explored in Chapter 2 are considered. The examples serve a dual purpose, that of unpicking different representations, and of setting the data in some useful context pertinent to the subsequent analytical chapters of the thesis.

3.2 Representing Geographic Information

3.2.1 Quantitative Geography and Representation

The way in which we choose to represent geographic information nowadays is unquestionably linked to the development of the discipline of quantitative geography, in the 1960s. David Harvey's "Explanation in Geography" (1969) served as a milestone in the era's shift from a focus on regional studies, to a positivist philosophy that sought to innovate a new geography based upon location theory, understanding spatial patterns, and creating generalisable spatial rules. The most notable rule to come out of this quantification of geography is known as "Tobler's First Law of Geography" and it contends that:

"Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970 p.236)

This kind of thinking was soon cast as "spatial science", and was epitomised by textbooks on "locational methods" (Haggett et al, 1977) and "quantitative geography" (Wrigley and Bennett, 1981) that emphasised representation within a rigid, formally defined, universal spatial structure. Such an approach to representation is important in taking a scientific attitude to Geography, in which results must be reproducible, and capable of being assessed as significant or not. This condition is familiar to medical statistics, with Florence Nightingale (1820-1910) heralded as making a representational breakthrough in the statistical visualisation of deaths in the Crimea attributable to unsanitary conditions, which led to the emergence of modern nursing practice (Cohen, 1984). Similarly, Dr. John Snow (1813-1858), considered the father of modern epidemiology, used a spatial representation (Figure 3.1) of deaths due to cholera during an outbreak in Soho, London as evidence for his thesis that cholera was waterborne. As a result of removing the pump handle of the water pump that was the focus of the spatial pattern of outbreaks, the outbreak dissipated (Longley et al, 2011).

The advent of GIS, and its increasing uptake amongst a wider community, coupled with arguments in academia regarding its usage, led to Goodchild's initial suggestion of a "spatial information science" (1990) and his subsequent formalisation of "Geographic Information Science" (GISci: Goodchild, 1992). The purpose of GISci was to encourage a discourse that would support the developing usage of GIS, and help move practitioners away from the

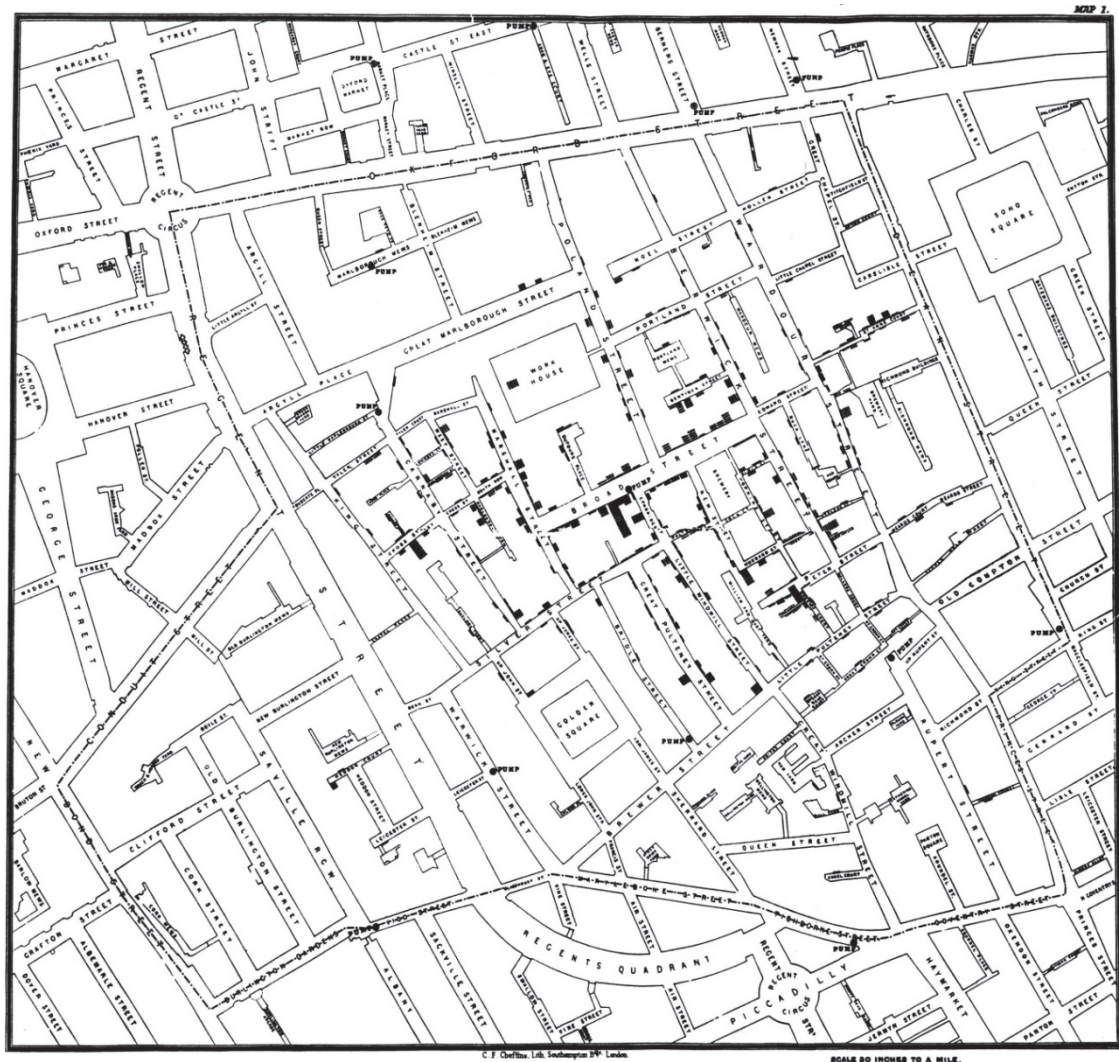


Figure 3.1: Dr. John Snow's map of cholera deaths in Soho (Snow, 1855)

prevailing view that GIS was simply a "tool" (Wright et al, 1997). GISci allowed an agenda to develop that sought to unpack some of the theoretical aspects of quantitative geography that had been left relatively unexplored (except perhaps by those that had primarily cast themselves as detractors to Spatial Science) in favour of model-building (or "tool-making" (Wright et al, 1997)). This led to the development of a set of standardised representations of geographic objects and fields, recently Goodchild et al (2007) were able to demonstrate that the representation of geographic information has a common syntax. Goodchild (2004) has argued that a continued interest in form, and representation of geographic phenomena, has led to a deficiency in the development of processes for understanding space. In this respect, a standard syntax offers the potential to move GISci beyond the mechanics of representation. However, in the context of spatially integrated social science, a consistent understanding of representation, subject to the field of enquiry, is a key precursor to further unpicking the spatial associations and processes inherent in social science disciplines. The

practicalities of representation in GIS are dealt with in the next section, subsequently the focus shifts to the implications of representation for research in health and medical geography.

3.2.2 Representation in GIS

There are two main conceptual ways of thinking about representing geographic data in GIS (from Longley et al, 2011), as objects and as fields. Defining geographic phenomena of interest as either discrete objects or continuous fields requires some forethought as to the preferred representational form. A discrete object view of the world infers that the geography of interest, at the spatial scale at which it is chosen to observe it, can be delineated in some way, that it has boundaries that are distinct from an otherwise abstract, limitless space. Conversely, a field view of the world suggests that the geography in question, at the scale of appreciation, is essentially unbounded, and that the best way to capture it is to define its specific value at every possible position in space. Examples of discrete objects include: buildings when viewed at the neighbourhood scale, or urbanised area when viewed at the city or regional scale; examples of continuous field data might include a representation of elevation – every point on the Earth's surface has a height relative to a predefined datum. Of course, the boundaries between objects and fields are not as distinct as could be hoped: it is easy to conceive of peaks, pits, valleys, ridges etc. as distinct topological features that can be encoded as objects from a continuous surface representation of the Earth; or it may be more convenience to represent urbanisation as a continuous surface based upon the density of concrete at all points on the Earth's surface, rather than a bounded and distinct object. Clearly some consideration is needed as to the type of representation that is appropriate for a given research agenda. One of the benefits of GIS is its ability to transform data from one type of representation to another. This is largely a product of the numerous ways in which it is possible to digitally represent the two conceptual approaches to representing geographic information.

In terms of digital representations, the concepts of objects and fields map to a digital encoding as either a vector or a raster. Vectors in their simplest form can be thought of as a coordinate pair, in the context of the data in Chapter 2 a coordinate pair might represent the centroid of an administrative district, or the residential building location of a patient. Vectors can be extended to include line segments, which become polylines when recorded as ordered strings of points in which a link between each point is implied; or polygons in

which the ordered string of points forming a polyline ends with the same coordinate pair as it starts with, forming a closed ring in which there is an implicit inside and outside. Points, lines and polygons form the basis of representing discrete objects in a GIS (Longley et al. 2011 p.88), and because their spatial location is specified subject to a predefined coordinate system their precision is theoretically only limited by the capacity of the computer to store it. This means that vectors do not have an implicit spatial scale, rather, one is implied by the accuracy of the recording of the spatial location, or the generalisation of the vector data itself. A raster is a regular grid of cells in which any one cell relates to a specified area on the Earth's surface. Each cell in a raster grid has an associated value representing the magnitude of a variable in that area, with the size the cells indicative of the resolution of the raster, and hence of the spatial scale. A raster is effectively an aggregation of all the possible values of a phenomenon within that cell, and as such it has a fixed resolution: it is possible to aggregate upwards creating larger cells, but not to disaggregate downwards to create smaller cells. There are several other forms of representation that have developed from work in GISci for particular purposes within GIS. These can include representations such as Triangulated Irregular Networks (TINs), for representing a surface in a vector form, graphs for representing routable networks of streets, or techniques for representing vague, or uncertain, objects. Dilo et al (2007) suggest the use of such objects in examining coastal erosion for example.

Goodchild et al (2007) formalise the conceptual and practical representations of spatial data by reducing representation to a single primitive called the geo-atom, a tuple of the form $\langle x, Z, z(x) \rangle$. In the tuple, " x defines a point in space-time, Z identifies a property, and $z(x)$ defines the particular value of the property at that point" (Goodchild et al, 2007 p. 243). A collection of geo-atoms can ably represent an object, while fields are representations of these geo-atoms over space. This maps directly onto the Longley et al (2011) statement that "geographic data link place, time, and attributes" (p. 81) and representations are inherently selective abstractions. Ultimately representational mode is the outcome of choice and convention, and choosing how to represent spatial data will affect the specific analysis options available. In order to make the appropriate choices, a consideration of how spatial concepts are treated in the domain of enquiry is required, and in this context the next section considers the articulation of geographic concepts within health and medical geography.

3.2.3 Health and Medical approaches to geography

The usual approach to spatial representation in health and medical geography is simply to use the representation prescribed by the available data and indicate the availability of techniques which offer value to the analysis of health data. This is the approach of Cromley and McLafferty (2002), who demonstrate how health researchers can use GIS, but not strictly how GIS should be used by health researchers. The distinction is perhaps an arbitrary one, however, it is important to expose the key aspects of geographic representation as it pertains to health and medical geography in order to best understand how to integrate health information in a GIS. In terms of the kind of quantitative research to be conducted using the data described in Chapter 2, there are two important aspects of geographic conceptualisation in health and medical geography to consider: place, and neighbourhood. These aspects are broadly congruent with Kearns and Moon's (2002) first and third applications of place: "place as a socially constructed and complex phenomenon" (p. 610); and "place awareness" (p. 611) particularly with reference to multilevel modelling. However the second application, pertaining to "landscape" is dropped from consideration as the holistic notion of a landscape in this context can only be captured qualitatively.

3.2.3.1 GIS, Health and Place

GISci considers that "the first component of an atom of geographic information is a place" (Longley et al, 2011 p. 149), and that a place can be unambiguously specified using a coordinate system "in a way that is meaningful to everyone" (de Smith et al, 2009 p. 58). This means that representing place in a GIS under the remit of GISci is as simple as recording a place (as a position in space) and affixing a measurable value to that place. Krygier (2003) notes that links between health and location have long been recognised in the literature, citing writing by the ancient Greek Hippocrates. Likewise, Friedrich Engels (1887) demonstrates the associations between disease outbreaks, location and the need for 'sanitary conditions' in towns and cities in "The condition of the working class in England in 1844". Medical geography, which has historically been linked with a spatial science approach to research, is naturally at home with the GISci approach to representation. Place, or perhaps more accurately 'location', has always been an implicit part of healthcare in the context of: resource allocation; hospital or healthcare service site selection; and accessibility and coverage studies (Tanser et al, 2010). The import of place has risen considerably in the last 10-15 years gaining traction politically and becoming a significant focus for the media.

This is evidenced by the stylisation of particular access inequalities as 'postcode lotteries', an evocative term that made its way into both government policy, such as the NHS Cancer Plan (DH, 2000), and academic writing (Bungay, 2005; Lyon et al, 2004). However, as has been discussed in Chapter 1, the evolution of health geography has redefined the distinctly quantitative approach previously advocated for place in medical geography, to something that is considerably more subtle, in line with the changes to human geography as a whole and the apparent 'cultural turn' (Barnett, 1998).

The preeminent comment on place and health comes from Kearns (1993) and Kearns and Moon (2002). Broadly, much has been made of the shift from medical- to health-geography (Kearns and Moon, 2002), Kearns (1993) identifies the inadequacy of a solely biomedical model of health in which conditions of ill-health and disease are foreground, identifying an intersecting socio-ecological model which necessitates a more interactive understanding of the relationships and reciprocities between a population's health and their social, cultural and physical environment. Kearns' (1993) work links a developing interest in place with the emergence of a 'post-medical' geography in which an analytical standpoint that emphasises spatial relationships between objects is rejected in favour of one which acknowledges the health-related characteristics of places themselves. In doing so Kearns' (1993) finds that medical geography, and the statistical, spatial science, viewpoint associated with it has led to a distinct detachment between health and place, treating them as separate domains rather than interdependent concepts. In terms of health, an understanding of place needs to capture a sense of experience and of uniqueness in order to be useful to health analyses.

Health analyses that privilege an experience of place owe something to the work of Foucault on medicine and habitat (Elden, 2007), who, in the birth of the clinic (Foucault, 1963), discusses three important spaces of disease, contingent to some extent on differing geographical scales, which are: the body, the family, and society. The latter, society, is where Foucault bases his reasoning for a shift in the way that medical knowledge is constructed, charting a movement by society to a situation in which medicine evolves as an empirical discourse founded upon an ordered and accepted way of seeing the body. Foucault termed these shifts "epistemes" and it is by way of a change in episteme in medical geography that place came to be an important component of the way in which health is understood. Another important episteme is described by Moon and North (2000), and it covers the birth

of the NHS in the 1940s as a national social welfare initiative which created a standardised approach to practicing medicine, and receiving medical care, in stark contrast to the previous disorderly set of private insurance providers.

Locative studies of health in a critical sense have included the discourse of 'healthy places' and 'therapeutic landscapes'. Frumkin (2003) defines 'healthy places' as places that have been designed and built, or are otherwise recognisable as being 'good' for people's health; 'therapeutic landscapes' share a similar distinction in that they denote places that have achieved a reputation for healing, or promoting well-being and maintaining health (Gesler, 2005). The ideas behind both themes involve a critical examination of how these landscapes or places formed and came to function interactively with social attitudes of health. It is at this point in thinking about place where it becomes distinctly difficult to view health information within a GIS – how can this apparently important criterion of experience be captured digitally? Such a question recalls Curry's (1998) statement in his treatise on place in GIS that "there are very substantial limits to what can be represented with a geographic information system" (p. 11) and Couclelis's (1992) warning that "the most significant geographic spaces may never make it into a computer" (p.76).

3.2.3.2 Neighbourhood Analyses in Health

Place as defined in the previous section has taken a substantially qualitative turn, which presents some significant representational challenges to GIS. That is not to say that quantitative health geographers cannot learn anything from such a valuing of place, indeed Macintyre et al (2002) seem to take such insights as a wake-up call, arguing that the effects of place are often seen as a residual category in analysis and that these 'place effects' are in need of further work to aid their understanding. Place-based effects are commonly formalised in analytical terms as neighbourhood effects, in which the health of an individual or community is subject to the place within which they live. Neighbourhood effects are important, with Kawachi and Berkman (2003) showing that studies have indicated a moderate, but significant, association between neighbourhood environment and health, and further suggesting that this effect may have been underestimated. Whilst it would be impossible to capture many of the intangible aspects of place, including those espoused by Massey (2005) for instance, it is certainly possible to treat place more sensitively within the framework of GIS.

Kawachi and Berkman (2003) outline several important considerations in neighbourhood analyses, of particular interest is the distinction between social selection and social causation. Social selection is defined by active residential preference, which may have an effect on the social make-up of a neighbourhood. This includes poor people choosing low-income neighbourhoods due to the availability of housing at low cost, or people belonging to particular ethnic groups preferring to live in areas that already have high ethnic minority populations. Kawachi and Berkman accept that this is certainly a process that is ongoing in residential neighbourhoods, however they also raise the distinct possibility of social causation in which some people have no choice at all, or indeed very constrained choice with regard to their residential neighbourhood. It is also important to note the message from MacIntyre et al (2002) that in considering place in terms of its effect on health, there is no empirically clear-cut distinction between the composition of a place - the way in which a population is arranged, and the place's context - the characteristics of an area which generate its composition. This means it is very difficult to definitively outline which features of a place, be it the physical environment or its socio-economic descriptors, actually have an influence on health.

One particular reason cited for the difficulty of dealing with place is the fear of encountering the 'ecological fallacy' (Macintyre et al, 2002) wherein the characteristics of individuals are inappropriately inferred from aggregate data (Longley et al, 2011). It may also be the case that trends in analytical techniques had an influence in this respect, with the emergence of exploratory spatial data analysis (esda) techniques (Anselin et al, 2006) or multi-level modelling (Duncan et al, 1998) driving the uptake of place-based analyses in health research. Macintyre et al (2002) offer the possibility that places have been neglected in health studies in favour of the previous political tendency to think in terms of the individual. It is thus possible to see the change from a Conservative to a Labour government in 1997, and the subsequent shift in NHS policy away from pseudo-marketisation to a paradigm of social choice and community, as a driver of the development of locative studies of health. It is also possible that a renaissance in area classification, and geodemographics (Longley, 2005), as part of a larger movement in Geography towards understanding people and places, has contributed to the increasing relevance of place to health. It is useful within the field of geodemographics to decompose place into two components, one locative and one pertaining to social similarity. The idea being that a quantitative understanding of a place

might be understood by considering the locative effects as the spatial dependence or spatial autocorrelation of a phenomenon – i.e. the additional information about a place that can be derived simply by looking at other adjacent or nearby places; whilst social similarity tells us something about the variation within that place, and how that variation contrasts with other places.

There are numerous approaches in the measurement of neighbourhoods that require justification in research. The most basic, and arguably the most difficult of these is the question: what is a neighbourhood? Selection of a neighbourhood will implicitly affect the substance of the analysis. For instance a neighbourhood can be conferred by the small areas defined for census dissemination in the UK, this opens up a large raft of socio-demographic data with which to characterise neighbourhoods. However, the form of such neighbourhoods is fixed, and cannot be accurately aggregated to new areas unless they use the lowest level neighbourhood as a building block. Conversely defining our own neighbourhoods, which may be empirically more sound, means having to aggregate data to these bespoke areal units, if the available data for this process are limited it may mean missing out of some important variables. Indeed, even if a practical definition of a neighbourhood can be resolved, the issue comes full circle to the question of how it can be represented in a GIS.

3.2.3.3 Consolidation: Representing Health and Place in GIS

Kearns and Moon (2002) note that the geographies of health are becoming a 'braided river' in which an increasing number of connections are being made with a body of discourse outside of the traditional remit of medical geography. Given its history, and the undoubted importance of statistical data to most forms of health research, it is likely that a more overtly mixed-methods approach will define the new health geography. It is clear that in a climate of public health that increasingly emphasises the possibilities of community-based care, the wider role that primary care could have in treatment, and patient choice; a more nuanced idea of place and its role in people's lives is needed. As discussed in Chapter 1, engaging with a discourse of spatially integrated social science, as advocated by Goodchild and Janelle (2004), is a step on the road towards achieving a more complete view of health and healthcare research.

GIS offers real possibilities to expand upon understandings of place in health, however it is not a clear cut situation, and much will depend upon using the appropriate spatial representation. Moreover, there will have to be a sense of compromise between the implicit usage of a GIS, which concerns abstracting and simplifying the real world in order to reveal patterns and associations in greater relief, and the implied goal of health geography of capturing as much of the complexity of place as possible in order to better understand health, and healthy environments. GIS will never be able to fully capture place in the sense intended by qualitative thinkers, but certainly work with GIS will allow a fuller realisation of the texture of place, and a steady opening up of digital conceptualisation and representation of neighbourhoods (cf. Cope and Elwood, 2009). Further, it is the ability to generalise and abstract conceptualisations of, and awareness of, place that allows for directed research on the likely efficacy of healthcare interventions or policies. This occurs across the NHS as a whole, whether the space in question is the body- as might be the case surgically- or the society- as occurs through the provisioning and spatial planning of healthcare. Certainly, from a policy perspective, the ability to integrate data about the surrounding environment into analyses of health inequalities will allow a re-evaluation of the priorities in healthcare, and lead to the development of better provision in primary care and more effective service for communities.

In the next section, a practical approach is taken to representing health data, with examples focusing on what can be gained through different representations of the Southwark patient register data.

3.3 Practical Representations of Healthcare Information

3.3.1 Views of Southwark

The most straightforward use of representation is to create a view of a particular set of geographic information. Figure 3.2 presents a general map of Southwark with all data represented as discrete objects: the intent is to communicate to the map viewer the spatial structure that pertains to the built environment. In a sense, this map portrays a view of the place that is Southwark, but only in a very shallow way, although many such issues are the remit of critical cartography (cf. Crampton and Krygier, 2006). Much has been done in creating this view to promote clarity, this is achieved by abstracting and reducing the

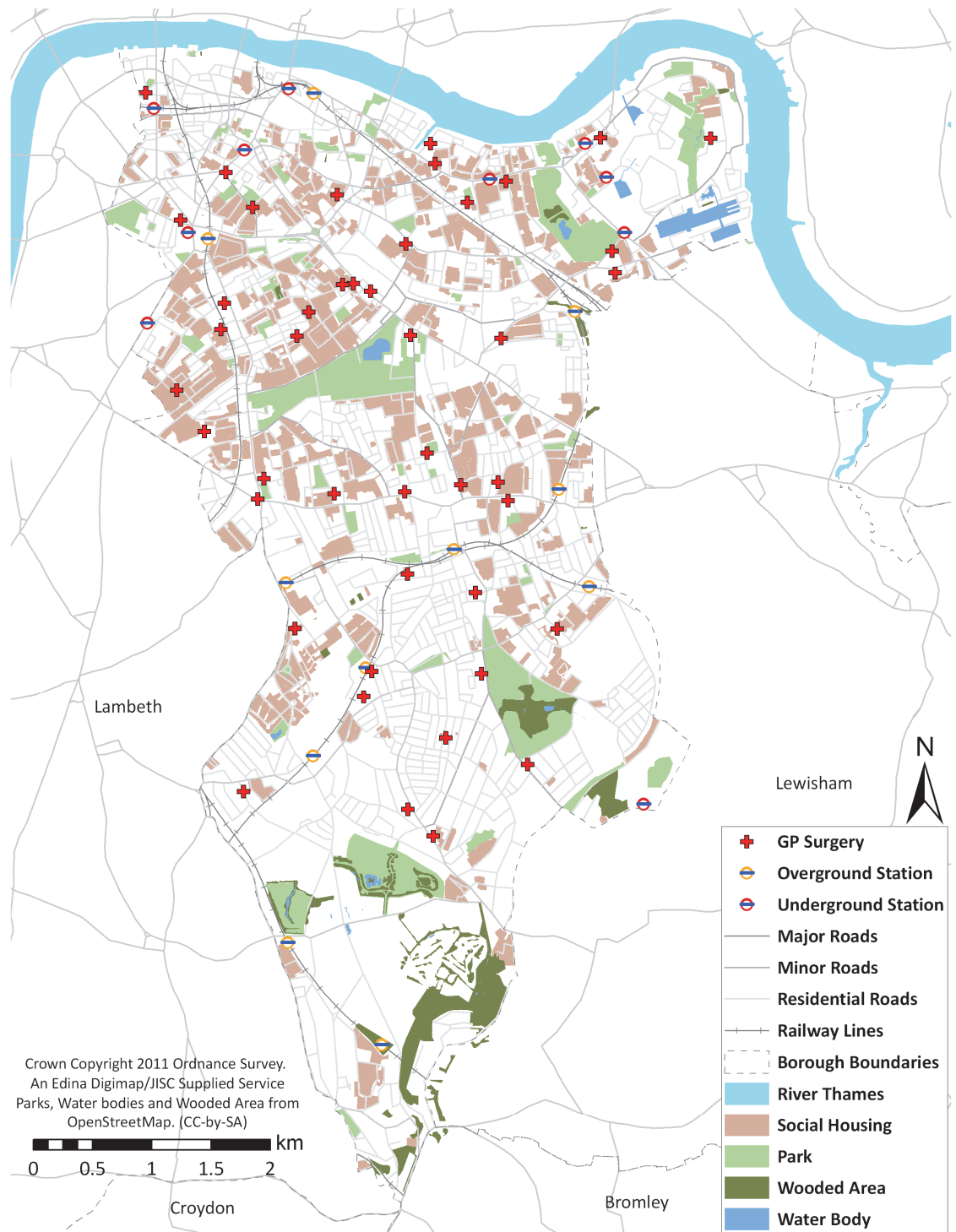


Figure 3.2: A contextual view of Southwark, detailing the spatial structure pertaining to elements of the built environment.

number of different aspect of place that exist, as such it is a sample of reality. However, it is important to realise that what is shown is based on the express decision of what it is important to show from the perspective of the map-maker, the included objects provide a basis for visual comparison with other views of Southwark. In Figure 3.3, for instance, it is

possible to visually infer an association between high population density, and presence of social housing in Figure 3.2.

In Figure 3.3, both views are based on a common representation of people in the Southwark patient register, in which they are geocoded, as in Chapter 2, to their household. However, with c.300,000 people a view which simply uses a point-based representation does not hold much value, it will be difficult to infer the actual numbers, or density, of individuals in any given location as points will interfere with, and overlay other points. Using a GIS, the representation can be transformed into something that is more useful to the viewer, the view in Figure 3.3.A is of a raster surface representation of the population density with 25m by 25m cells, whereas 3.3.B is a vector representation using predefined 100m by 100m zones. Both of these representations are able to communicate something about the distribution in Southwark of patients registered to a GP surgery, but they do so in different ways. The key similarity is that both representations are aggregations, but it is the nature of aggregation that differs: the kernel density estimation (KDE) used in 3.3.A is a technique for approximating the continuous form of the probability density function (PDF) of the point distribution in question (de Smith et al, 2009 p.174), as such it is attempting to record a value for population density at every point in space. Figure 3.3.B is the spatial joining of point data to a predefined set of areal units (in this case square zones), the values are the result of a point-in-polygon operation (Longley et al, 2011 p. 59) which counts the number of people falling within each zone. The KDE technique requires a bandwidth to work, essentially smoothing the point distribution upon which it is based, and the resulting raster representation is a smooth surface, whereas the areal aggregation is discrete, there is no smoothing, just a shift in spatial scale, thus we know that cells with a non-zero count definitely contained at least 1 person – this same assumption cannot be made with the KDE surface.

The next section takes the idea of being able to have multiple representations of the same underlying data further, using some traditional approaches to measuring spatial equity as a way of illustrating how different approaches to conceptualising spatial equity can lead to different representations.

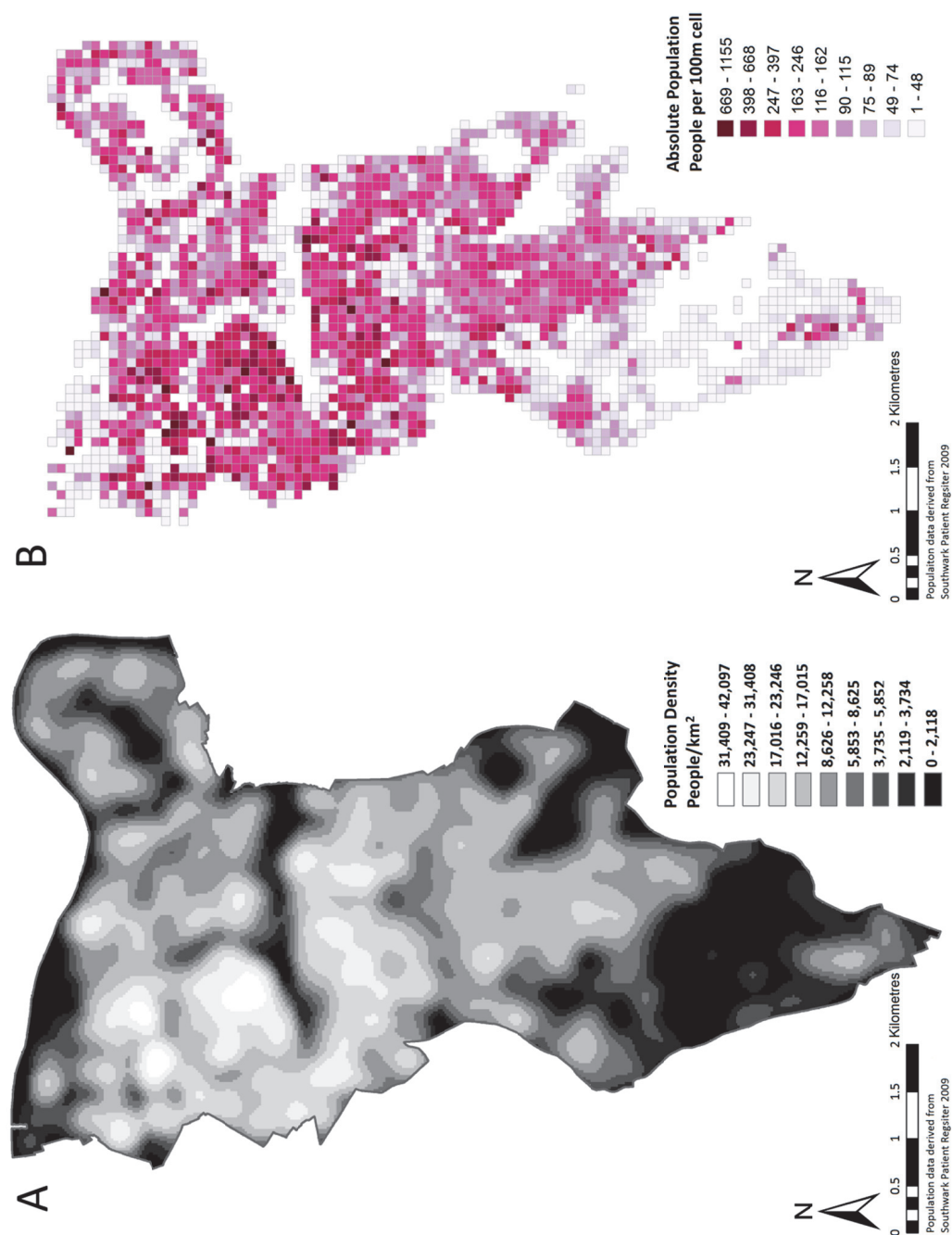


Figure 3.3: Two representations of Southwark population derived from the NHS Patient Register. A) uses KDE whereas B) is a simple aggregation.

3.3.2 Representations of Spatial Equity

The idea of spatial equity, as a component of healthcare equity, has been discussed in detail in Chapter 1, suffice to say it is a measure of the “fairness” of the spatial distribution of services. In this section, three different ways of representing spatial equity are considered: buffering approaches, potential models, and density models (following Truelove, 1993; Talen and Anselin, 1998, Ricketts et al 1994; and McLafferty and Grady, 2005). Each of these approaches has at its heart an attempt to capture variations in accessibility; however, the issue of the measuring “fairness” is a far thornier issue than can be answered in this thesis.

3.3.2.1 Buffering Approaches to Spatial Equity

This approach to viewing spatial equity is the simplest, it involves drawing a buffer of some prescribed length around service sites and seeing which areas fall within the buffer and which do not. The approach allows the question of how many GPs can be visited within x metres; however it requires knowledge of the numbers of GP at each surgery. This method emphasises the number of choices available in any given place. Imagining that a 10 minute walk is an acceptable distance to travel, 800m buffers are drawn equating to a walking speed of 4.8 km/h or 3 miles/hour. There are many different ways in which this data could be represented, here using the same 100m grid as in Figure 3.3.B, but it could also be estimated based on the point locations of patient households, for instance.

The difference between Figure 3.4.A and 3.4.B is the way that distance is used in the buffering procedure. In Figure 3.4.A distance is assumed to be Euclidian, this requires a classically isotropic representation of space, in which there is a uniformity of access to a given point from all other points. This is the reason that there appear to be circular outlines in the map view. Figure 3.4.B used a network representation of the roads from the Ordnance Survey’s ITN (Integrated Transport Network) data, in order to constrain access to service locations, in this case distance is anisotropic, access to a given service location is easier from some direction than others based on the road network. The network distance buffering approach reveals a similar pattern of access to a GP as the Euclidian distance approach, however the number of accessible GPs is reduced, and this is evident as both views use the same classification scheme. It seems likely that the Euclidian approach is overestimating the accessibility of patients to GPs, which may be important in the context of analysis conducted at the local scale, as primary health care services are inherently location-based and community orientated. In Figure 3.4 both Southwark and non-Southwark GPs

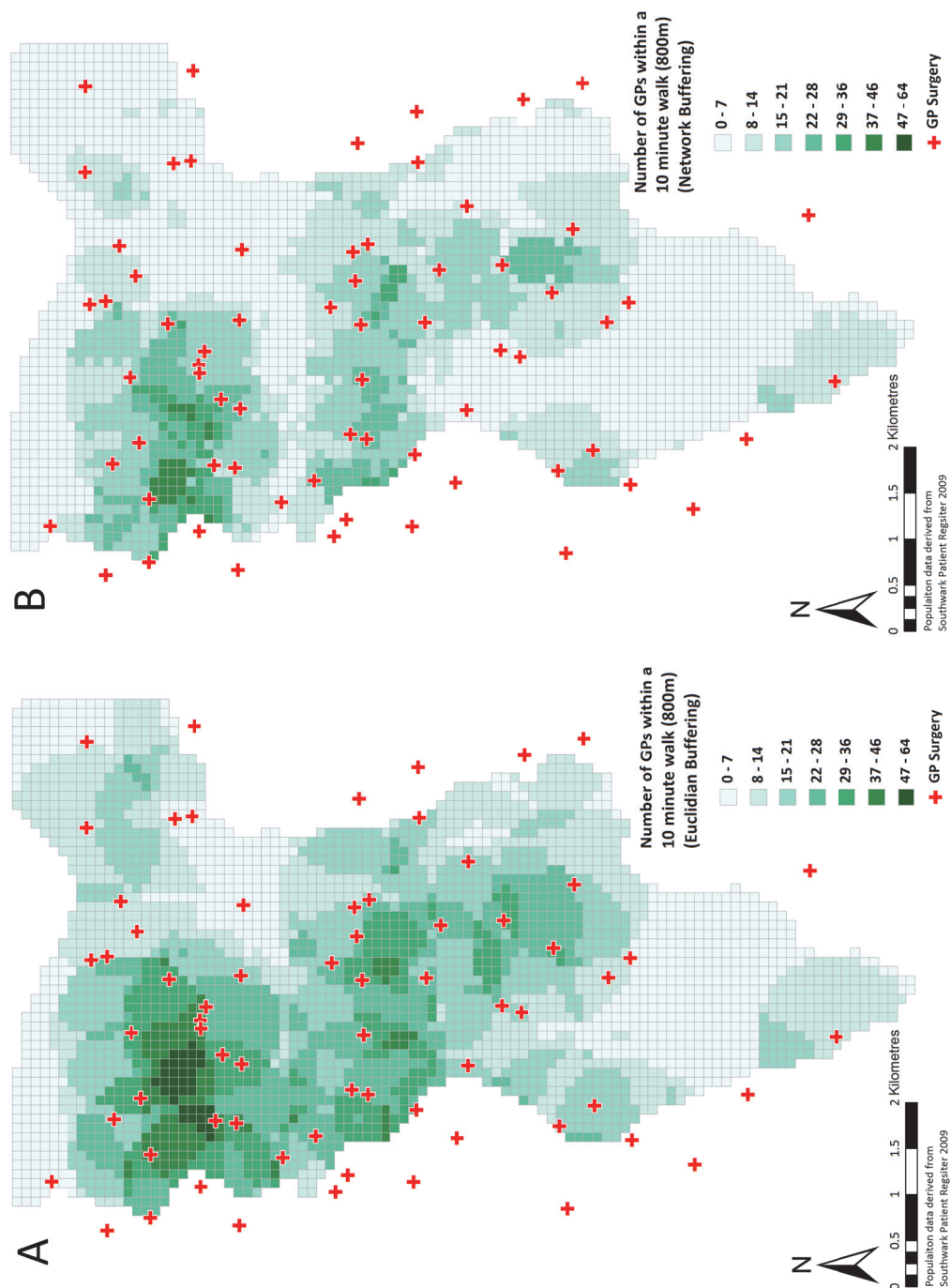


Figure 3.4: Access to GPs in Southwark using a buffering approach that favours A) Euclidean distance and B) Network Distance

have been included to avoid edge-effects in the view, it would be possible to characterise the effect of PCT boundaries by accounting for accessibility to Southwark and non-Southwark GPs. There are other ways of constraining access, such as by public transport accessibility, which would again create a different view.

3.3.2.2 Potential Model Approaches to Spatial Equity

Rich (1980) defines the potential model as “an index of the intensity of possible interactions between social or economic groups at different locations” (p. 3). Chapter 1 introduced the idea of “interaction” as key to a spatial understanding of access. In terms of measuring spatial equity, we can specify that the interaction accounts for all possible flows to a GP surgery, and as such it is a measure of opportunity for interaction between people in different areas, and a service. A potential model is in a sense a revision of the buffering approach, in which rather than specifying a binary indicator of whether an area, or person, is within (and hence served) or outside of (and hence un-served) a GP surgery’s service area, a distance decay function is specified to account for the “friction of distance” implicit in accessing a service. Talen and Anselin (1998 p.600) specify a population potential model as:

$$Z_i = \sum_j \frac{S_j}{d_{ij}^\alpha} \quad (3.1)$$

In which the potential accessibility Z at location i is equal to the size (S) of a service (j) over the distance between location i and service j subject to a distance decay α , summed for all services.

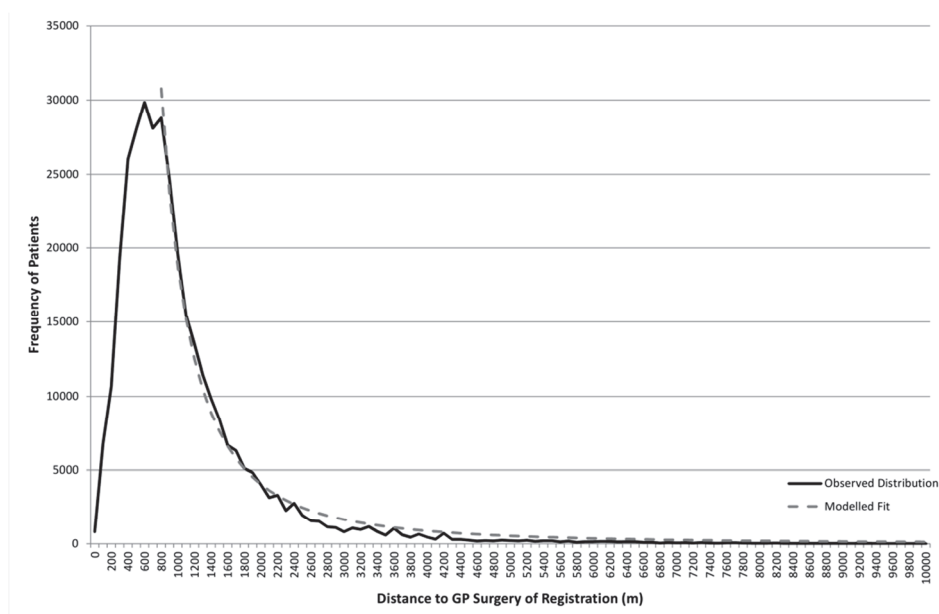


Figure 3.5: Distance decay curve of patients registering with GP surgeries in Southwark.

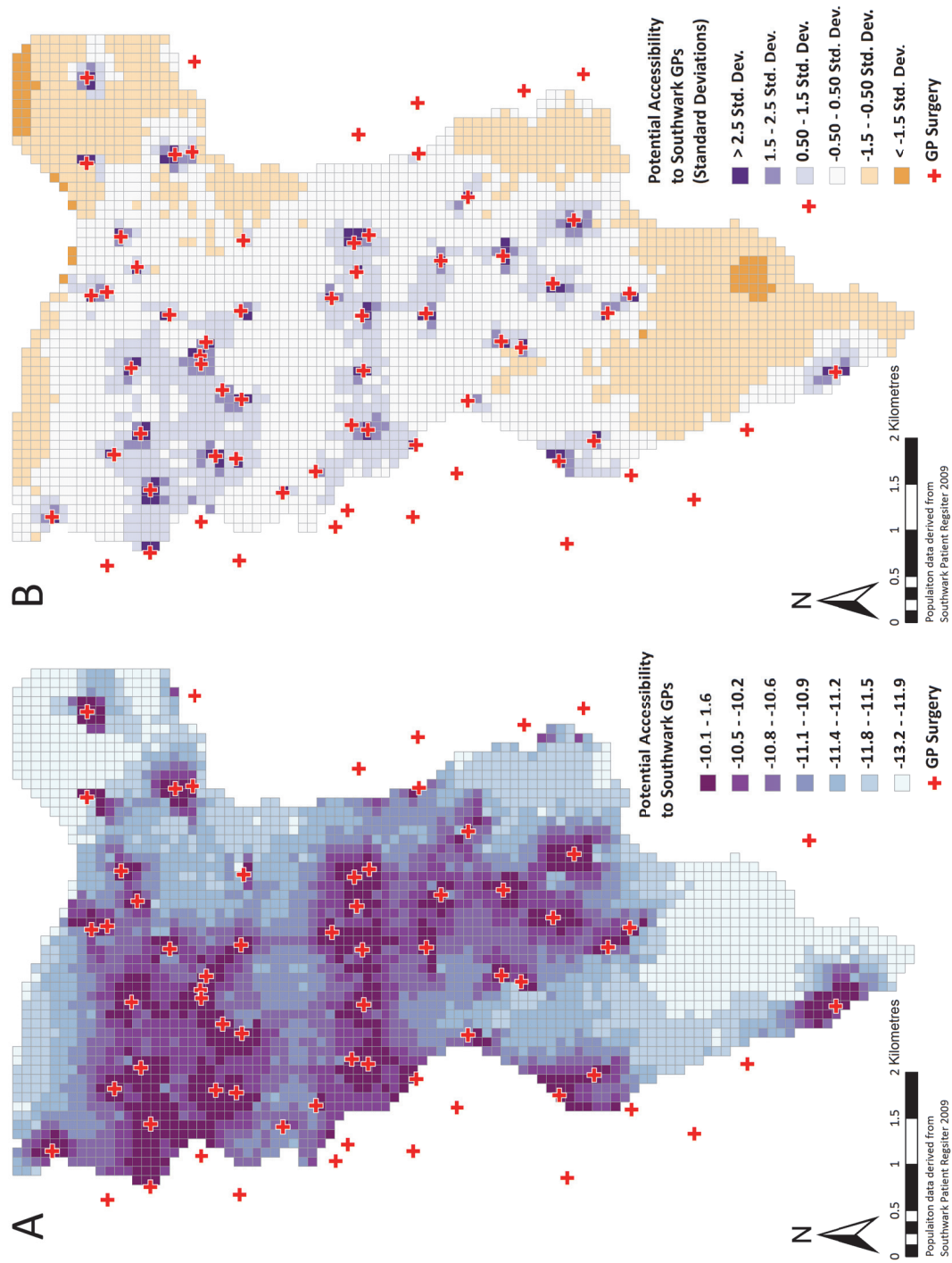


Figure 3.6: Maps of Potential Accessibility where A) is classified by septiles of the log of the potential accessibility and B) is the Standard Deviations of A

The key aspect of this model is setting an appropriate α value to represent distance decay: whilst a squared term is most commonly used, it is also possible to set a value based upon empirical evidence. To do this the network distance distribution of patients accessing all GP surgeries in Southwark is considered (Figure 3.5), and a best-fit estimate of α is obtained. The distribution of patients registering with GP services as per Figure 3.5 follows a log-normal distribution, but because the interesting aspect of the curve is the decay, a power law (in this case proving a better fit than a negative exponential) is fitted to that aspect of the curve, the fit returns an R^2 of 0.992 and the resultant α is 2.2. Figure 3.6 demonstrates the output of the potential model.

The output values from the potential model form a positively skewed distribution, which can be normalised by taking the logarithm all values. This gives rise to Figure 3.6.A which shows septiles of potential access to GPs in Southwark, further, because the distribution of data values has been transformed, the standard deviations of the data can be represented. Assuming that the mean potential to access a GP is a useful baseline measurement, Figure 3.6.B shows areas which are well served, and areas which are effectively underserved.

3.3.2.3 Density Estimation Approaches to Spatial Equity

Kernel density estimation (KDE) is a data smoothing technique, for a given point pattern it is an effective way of estimation the probability density function of that distribution. When applied to 2-dimensions, it can be interpreted as “spreading” a phenomenon, represented as a point, over a surface, subject to a pre-specified kernel shape. The type of kernel used defines how the point is spread across the surface; a Gaussian kernel will effectively spread the point in a normally-distributed way. As such, kernel density estimation can be seen as a way of approximating a distance decay effect in accessing a service, as the kernel implements a decay-like effect. In the case of Figure 3.7, the actual kernel used is an Epanechnikov kernel which, unlike the normal distribution which is asymptotic to 0, is bounded and hence has a finite extent. The kernel function is as follows (de Smith et al, 2009 p.176):

$$f(t) = \begin{cases} \frac{3}{4}(1 - t^2), & |t| \leq 1 \\ 0, & t > 1 \end{cases} \quad (3.2)$$

Bandwidth is an important consideration in choosing a kernel, as it defines the upper extent to which a phenomenon will be spread. When applying kernel density estimation to

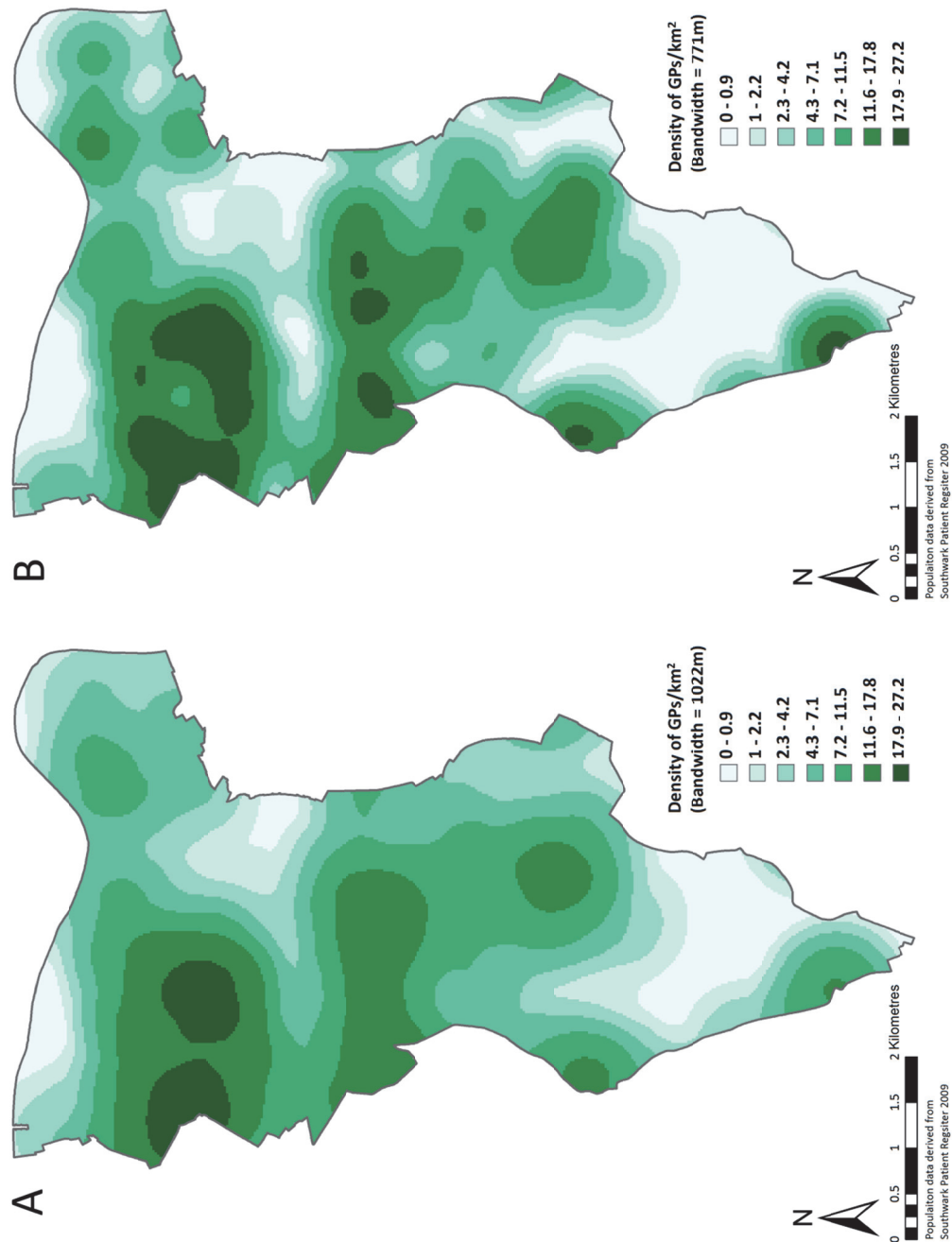


Figure 3.7: KDE of GPs/km², A) uses a 1022m bandwidth and B) a 771m bandwidth, based upon the mean and median distance travelled to GP surgeries (Fig. 3.5)

population density in Figure 3.3, the important question is: what is the bandwidth value that is optimal for smoothing the underlying point pattern? The idea here is that the continuous surface be as good a representation of the point distribution as possible. However, in terms of measuring accessibility the intent is somewhat different, although the methodology is the same. The appropriate bandwidth for this task is likely to be larger than the bandwidth used in Figure 3.3.A because the services in question should have a wider influence than an individual in a population density surface. Two bandwidths are considered for use in the kernel density estimation process, and are derived from Figure 3.5. Firstly, the mean distance that patients are willing to travel to their GP surgery of registration, and secondly, as the distribution in Figure 3.5 is positively skewed, the median distance is also tested. There is a broader consideration of kernel density estimation and bandwidth selection later in Chapter 6.

Unlike the previous examples in Figures 3.4 and 3.6, the kernel density estimation is represented as a raster image with 25m by 25m cell size. What is evident is the broad similarity that this approach demonstrates when compared to the other approaches. Having created these alternative views of spatial equity, these views can all be brought together to learn something about how levels of spatial equity vary by different population groups.

3.3.2.4 Spatial Equity in Southwark

In each of these cases, the value for spatial equity can be joined to the individual, and then descriptive statistics can be generated for the dimension of interest. Similarly, the values can also be aggregated to another areal geography and compared to area-based statistics. Using the data from the Southwark patient register, the GP densities from Figure 3.7 A and B, and the population density in Figure 3.3 A, are joined to patients based upon spatial location and a simple OLS regression is used to investigate the relationship between this measurement of spatial equity, and patient characteristics. The regression is specified as:

$$SpatialEquity_i = \beta_1 AgeBand_{i1} + \beta_2 Female_{i2} + \beta_3 SwkOnomap_{i3} + \beta_4 SocialHousing_{i4} + \beta_5 PopDense_{i5} + \varepsilon_i$$

(model 1, A for Figure 3.7.A and B for Figure 3.7.B) or

$$SpatialEquity_i = \beta_1 LifeStage_{i1} + \beta_2 Female_{i2} + \beta_3 SwkOnomap_{i3} + \beta_4 SocialHousing_{i4} + \beta_5 PopDense_{i5} + \varepsilon_i$$

(model 2, A for Figure 3.7.A and B for Figure 3.7.B)

Where:

SpatialEquity = density of GPs/km² as defined in Figure 3.7 A & B

AgeBand = patient age in bands 0 – 16, 17 – 30, 31 – 45, 46 – 60, 61 – 75, 76+

Female = patient sex

SwkOnomap = patient ethnicity derived from Onomap as per Chapter 2.3.10

SocialHousing = whether the patient lives in Social Housing as defined by Southwark Council

PopDense = population density defined in Figure 3.3 A

LifeStage = lifestage classification as per Chapter 2.3.9

Two models with variable specification were considered implementing either patient age or household lifestage, as these two variables were correlated and their inclusion in a single model together produced some multicollinearity. Population density is included as a control in the model as it is highly spatially correlated with GP density (the spatial equity measure) on the basis that it is inefficient to locate GP surgeries where few people live. Concerns that there might be correlation between population density and social housing were alleviated when post-estimation of VIF (Variance Inflation Factor) for each model suggested that there was no severe multicollinearity in the models so both variables are included. The indicator of whether a patient lives in social housing or not can be seen as a crude binary indicator of socio-economic status – in a way analogous to the use of “free school meals” in schools-based research. The results for the models are given by Table 3.1.

The first thing to note is that the R^2 for each model is small, and in fact the majority of it is contributed by the population density variable. The point is to investigate varying relationships within demographic groups, not to attempt to explain why there is a variation in access to GPs. That spatial equity would be directly influenced by the contemporary distributions of patients is unlikely, since the location of surgeries in Southwark has historic roots, centred on providing a service available to everyone in the Borough. It is for this reason that spatial equity can be explained in a large part through contemporary population density: however a shortfall occurs because of changes in population distribution in the period since many of the surgeries were set up, the competing private interests of the GPs themselves, and other circumstantial factors, such as availability of premises.

Perhaps the most interesting aspect evident in the model is the effect of population density, in principle, those people living in social housing have greater opportunity to access health care services in Southwark simply because there are more surgeries closer to social housing

	Model 1 A		Model 1 B		Model 2 A		Model 2 B	
	B (Std. Err.)	t (sig.)	B (Std. Err.)	t (sig.)	B (Std. Err.)	t (sig.)	B (Std. Err.)	t (sig.)
Female	-0.093 (0.015)	-6.18 (0.000)***	-0.105 (0.019)	-5.46 (0.000)***	-0.072 (0.015)	-4.78 (0.000)***	-0.083 (0.019)	-4.31 (0.000)***
Age 0 – 16 (Age 31–45 = base)	-0.229 (0.022)	-10.22 (0.000)***	-0.281 (0.028)	-9.85 (0.000)***				
Age 17 – 30	0.039 (0.021)	1.89 (0.059)*	-0.009 (0.026)	-0.36 (0.716)				
Age 46 – 60	-0.028 (0.023)	-1.24 (0.215)	-0.003 (0.029)	-0.11 (0.911)				
Age 61 – 75	-0.066 (0.031)	2.10 (0.036)**	0.091 (0.040)	2.30 (0.021)**				
Age 76+	0.188 (0.043)	4.36 (0.000)***	0.274 (0.055)	4.99 (0.000)***				
Lifestage 1 (Lifestage 7 = base)					0.449 (0.089)	5.03 (0.000)***	0.110 (0.113)	0.97 (0.332)
Lifestage 2					-0.036 (0.103)	-3.49 (0.000)***	-0.525 (0.131)	-4.00 (0.000)***
Lifestage 3					0.042 (0.031)	1.36 (0.175)	0.014 (0.039)	0.36 (0.717)
Lifestage 4					-0.518 (0.043)	-11.97 (0.000)***	-0.670 (0.055)	-12.19 (0.000)***
Lifestage 5					-0.355 (0.079)	-4.47 (0.000)***	-0.420 (0.101)	-4.14 (0.000)***
Lifestage 6					-0.346 (0.131)	-2.65 (0.008)***	-0.683 (0.166)	-4.10 (0.000)***

Lifestage 8		-0.289 (0.025)	-11.65 (0.000)***	-0.316 (0.031)	-10.03 (0.000)***
Lifestage 9		-0.319 (0.031)	-10.39 (0.000)***	-0.392 (0.039)	-10.03 (0.000)***
Lifestage 10		-0.215 (0.032)	-6.63 (0.000)***	-0.240 (0.041)	-5.83 (0.000)***
Lifestage 11		0.002 (0.052)	0.03 (0.973)	-0.048 (0.067)	-0.73 (0.467)
Lifestage 12		0.043 (0.026)	1.82 (0.068)*	-0.044 (0.033)	-1.33 (0.183)
Lifestage 13		-0.043 (0.028)	-1.50 (0.133)	-0.039 (0.036)	-1.07 (0.283)
Lifestage 14		0.211 (0.066)	3.18 (0.001)***	0.323 (0.084)	3.83 (0.000)***
Lifestage 15		0.091 (0.042)	2.19 (0.029)**	0.055 (0.053)	1.04 (0.297)
African (British = base)					
E. Asian	-0.141 (0.026)	-5.46 (0.000)***	-11.18 (0.000)***	-0.109 (0.015)	-10.44 (0.000)***
E. European	0.194 (0.046)	4.19 (0.000)***	1.65 (0.100)	0.196 (0.046)	1.56 (0.118)
European	0.177 (0.052)	3.41 (0.001)***	2.09 (0.036)**	0.198 (0.052)	2.24 (0.025)**
Hispanic	0.033 (0.023)	1.46 (0.145)	-0.71 (0.475)	0.040 (0.023)	-0.65 (0.519)
Muslim	0.290 (0.041)	7.00 (0.000)***	3.44 (0.001)***	0.314 (0.041)	3.75 (0.000)***
	0.316 (0.027)	11.91 (0.000)***	6.43 (0.000)***	0.347 (0.027)	7.06 (0.000)***

S. Asian	-0.117 (0.058)	-2.02 (0.044)**	0.022 (0.074)	0.30 (0.762)	-0.112 (0.058)	-1.93 (0.054)*	0.021 (0.074)	0.29 (0.776)
Other/Unclassified	0.115 (0.040)	2.91 (0.004)***	-0.013 (0.050)	-0.25 (0.802)	0.130 (0.040)	3.28 (0.001)***	-0.008 (0.050)	-0.16 (0.876)
Social Housing	-1.372 (0.017)	-81.15 (0.000)***	-1.910 (0.025)	-88.96 (0.000)***	-1.357 (0.017)	-79.83 (0.000)***	-1.893 (0.021)	-87.65 (0.000)***
Pop. Density	0.000445 (0.000001)	369.72 (0.000)***	0.000582 (0.000001)	379.35 (0.000)***	0.000447 (0.000001)	369.55 (0.000)***	0.000582 (0.000001)	378.95 (0.000)***
Constant	2.665 (0.025)	108.26 (0.000)***	1.1268 (0.031)	36.03 (0.000)***	2.714 (0.026)	105.23 (0.000)***	1.209 (0.033)	36.91 (0.000)***
Adjusted R ²	0.3358		0.3440		0.3367		0.3446	
AIC	1,637,026		1,779,476		1,636,704		1,775,757	
n	290,990							

Table 3.1: Regression results for relationships between Spatial Equity and some patient demographics for 4 models. Model 1 and 2 use an age categorisation and lifestyle respectively, A and B denote usage of Figure 3.7 A and B respectively as the continuous measure of spatial equity. *, **, * indicates significance at the 90%, 95% and 99% level respectively.**

estates than residential housing that is not social housing. However, when population density is controlled for, the relationship actually changes, with people living in social housing worse off than those that do not. This reflects the law of inverse care suggested by Hart (1971) that the availability of healthcare tends to vary inversely with need, in this context living in social housing is a crude indicator of need; this is effectively a socially determined health inequality as discussed by Marmot (2005).

The models all suggest that women have a lesser opportunity to access a GP than men, however the effect size is small suggesting that differences may not bear out in practice despite the apparent statistical significance, it is possible that different mortality effects might play a role here given women's tendency to outlive men. The age of the patient on its own does not seem to be as good a discriminator as the household lifestage, nonetheless, compared to patients of 31-45 (the most populous age band), young people and elderly people 61-75 years old have a lesser opportunity to access GPs, whilst those older than 75 have a greater opportunity of access, this may owe to the placement of social care facilities. This suggests a distinction between households who have dependent children, and those who do not in terms of opportunity to access a GP. This bears out in model two using the classification of household lifestage; all the classes which capture households with dependent children (classes 2,4,5,6,8,9,10 and 13) have a lesser opportunity to access a GP than the base class of households with a 35-54 year old reference person with no dependent children, although this is not always statistically significant.

Finally, there are differences based on ethnicity as classified by Onomap (Mateos et al, 2011): by and large the British and European groups have similar opportunities to access a GP, with several other minorities (notably, Muslim, Hispanic and Eastern European groups) having better access than the British group. The South Asian and East Asian groups vary between better, or similar, access compared to the British depending on the model, however the African group is notably different to other groups. African patients have a significantly worse opportunity to access a GP than the British, and hence any other group, this is despite the fact that African groups tend to cluster in the centre of the Borough (see Chapter 4). This may be a result of the fact that African groups disproportionately tend to live in social housing (Figure 3.8), and the effect is likely to be similar to that discussed earlier with regard to population density and social housing.

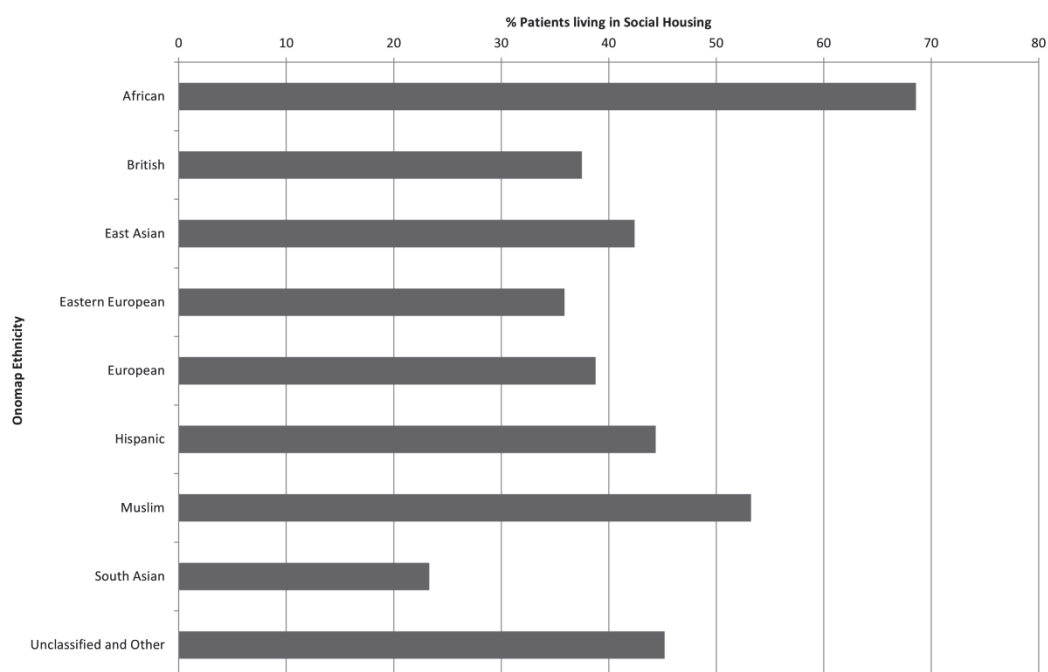


Figure 3.8: Proportion of each Onomap group living in Social Housing

There are numerous potential social determinants of health inequalities beyond those that have been investigated in this simple regression model. However, it does set up a base line understanding of the spatial condition of accessibility to a GP surgery in Southwark, articulated through a straightforward measurement of spatial equity. Undoubtedly, the measurement of spatial equity can be augmented in order to capture more dimensions of access, however it remains an indicator of the potential, or opportunity, to access a GP surgery. Chapters 5, 6 and 7 look to move beyond the idea of opportunity, using the Southwark patient register as an indicator of behaviour, suggesting that it can be used to represent the preferences of patients and hence shed light on the status of choice in primary care.

3.4 Consolidation

This chapter started by outlining how representations of geographic information are made, acknowledging that a fundamental part of what enables a scientific discourse of GIS is the rigour and formality with which these representations can be applied. The articulation of space and place in spatial science and GIS is also investigated, drawing an acceptance that recent formulations of space and place resultant from changes within the discipline of Geography have moved away from the kind of representations sought in GIS. A traditional approach to medical geography valued quantitative spatial science representations of

health, spurring on the growth of disease diffusion models in disease ecology or locational models of healthcare service provision, broadly embodying a spatial epidemiological approach. However, the evolution of health geography, as outlined in Chapter 1, has meant a far more nuanced approach to, and understanding of space and place, which is discussed in this chapter with reference to Jones and Moon's (2002) work. The evolving approaches to place in health, which emphasise place's relational nature as a "site of stories so far" (Massey, 2005) is problematic to a scientific GIS, as it is not necessarily flexible enough to capture the vagueness, ambiguity, multiplicity or qualitative aspects of place-based narratives.

The health data available to this thesis, as discussed in Chapter 2, conforms to the scientific underpinnings of GIS, using formal data sources, which are augmented in a suitably rigorous way so as to preserve the potential for statistical explanatory power held within. However, there is also an acknowledgement that in thinking about health and healthcare there are some important alternative and complementary ways of seeing the world. Where notable progress has been made in representing additional facets of place, such as in ordering compositional and contextual elements of neighbourhoods, or in the development of a texture of place, such ideas are integrated into the analytical approach to the thesis.

Undoubtedly, the capacity of GIS as a formal, scientific, instrument to engage with more experiential aspects of place is limited by the need to create a standardised, formal, mutually exclusive set of rules for representing any given piece of spatial information. GIS, will never be able to capture some of the elements of discourse related to therapeutic or healing landscapes, however there is an increasing opportunity to think more about, and conceptualise space and place appropriate to the discipline of enquiry. How place is naturally articulated in health enquiries may dramatically differ from other social or physical sciences and hence the type of representation in GIS, and its explicit meaning will require consideration.

The chapter moves on to illustrate some approaches to representation, using data on the London Borough of Southwark. This serves three purposes. Firstly it acts as a demonstration of alternative ways of representing some of the available spatial, and spatial health, information used in this thesis. Secondly, it serves to act as a milestone for thinking about what it actually means to represent health information in different ways, and how different ways of manipulating and analysing the health information can lead to expressly different interpretations of the representation, and resultant views of, the information. Finally, it

provides some contextual insight into both, traditional approaches to thinking about spatial equity in health analysis, and the status of healthcare in Southwark as it stands.

This practical exploration of representation enforces a number of important aspects that are applicable throughout the thesis. There is often a distinction between what is being measured, and what it is hoped that this measurement is a proxy for. The measurement of spatial equity ably represents this –spatial equity is the condition of equality of access to a service subject to need, however this is the modelled in these examples as the spatial variations in GP accessibility, thus it is possible to say that in some sense all these measures really describe is the objective opportunity, or potential, to access a GP, in a system in which distance is the only constraint. However, this abstracting of a complex and contested concept, such as spatial equity, presents an important starting point to distinguishing where social inequalities with regard to healthcare rest. In fact, in determining these social inequalities, there are several assumption being made about the nature of need for healthcare, and the social differentiation of that need, in its own right; need is an important facet of healthcare provision that is notoriously difficult to capture effectively in a quantitative manner.

By exploring the representation, and viewing, of health information, the chapter is ultimately able to uncover some tentative relationships directed at the opportunity for residents of Southwark to access primary care GPs. Such exploratory analyses and understandings of the context local to provision of healthcare are fundamental to providing an effective, efficient and equitable service. The theme of spatial equity and demographic variations in opportunity in Southwark are investigated further in Chapters 5, 6 and 7. In the next chapter, however, the possibility of using health information to capture something pertinent to the local context of healthcare is expanded upon, using the Southwark patient register to reveal a view of ethnic segregation and ethnic mixing in Southwark.

4 Ethnic Segregation and Structure in Southwark, London.

4.1 Introduction

The Southwark Patient Register, as a contemporary record of patient registrations with General Practice (GP) surgeries, offers a unique data source in terms of a near-real time record of population data, and is regularly used in aggregate form by demographers (e.g. Dennett et al, 2007; Boden et al, 1992). The patient register itself contains information on all people living within Southwark that are registered to a GP surgery within Southwark or otherwise. The only significant blind spots stem from the fact that registration is not mandatory, and therefore the patient register misses out patients who choose not to register with a GP surgery. Additionally, there may be some amount of inflation of the patient register due to the lag time incurred in being removed from a GP's practice list, as detailed in Chapter 2.3.1. However, this is still an extremely valuable insight into the contemporary patterning of population, one that is unavailable anywhere else in the UK; although the ONS do release estimated population counts at the small area level. Given the augmentation of the Southwark Patient Register data, as a dataset geocoded at the household level and with an indicator of ethnic, cultural or linguistic origin derived from patient forenames and surnames using Onomap, there is possibility to look further at spatial segregation in Southwark at an unprecedented level of spatial resolution.

Meaningfully capturing the characteristics of an area with respect to ethnic residential segregation has long been an objective of the social sciences, and is particularly important to an understanding of social justice and welfare. The standard quantitative way of calculating a measure of segregation is to derive an index, taking the ratio of one particular group in an area with reference to another group or the population as a whole. Over time different indices have proliferated and reviews such as Duncan and Duncan (1955) suggested that all related in some way to a conceptual "segregation curve" and mathematically demonstrated their interrelatedness. Early on, the index of dissimilarity, which captured much of the information contained in the segregation curve was adopted as the standard for assessing such issues, despite it not being a "perfect tool" (Taeuber and Taeuber, 1976). Nonetheless, indices alternate to the index of dissimilarity had continued to proliferate, leading to a "state of theoretical and methodological disarray" (Massey and

Denton, 1988 p.282) in which the preeminence of dissimilarity as *the* measure of segregation gave way to Massey and Denton's (1988) identification of specific indices as belonging to, and describing, particular dimensions, or aspects, of segregation, these were: evenness, exposure, concentration, centralization and clustering. This owed much to work by James and Taeuber (1985) who demonstrated empirically that exposure indices measuring the likelihood of interracial contact or isolation were distinct from segregation indices.

More recently, the underpinnings of segregation indices have moved from the binary consideration of White and Black, or White and Hispanic groups to a more general approach to ethnicity that accounted for segregation between multiple groups. Reardon and Firebaugh (2002) suggest that this owes much to the inadequacies of using a two-group segregation index in a world that is increasingly racially diverse. The diversification of indices was also marked by increasingly innovative attempts to accommodate space: traditionally an index was calculated almost arbitrarily over a set of predefined areal units which represented a particular, often administrative, aggregation of the population. This in mind, creators of segregation indices started to adjust for spatial aspects such as area, length of shared border, shape, and proximity (White, 1983; Wong, 1993; Reardon and Firebaugh, 2002; Brown and Chung, 2006), before Reardon and O'Sullivan (2004) demonstrated that a kernel density-based approach could usefully account for spatial segregation without the implied need for precomputed areal units.

The intent of this chapter is not however to add to the huge canon of indices and measures, nor is it to critically favour the production of one index over another; rather it takes the form of an applied study in interpreting, and in particular visualising the outputs of using such measures. Firstly, we have to spend some time understanding the historical context for segregation in Southwark; subsequently, a basic understanding of ethnic concentrations in Southwark is gleaned from the patient register using Location Quotients (LQs) with a kernel smoothing approach. Next, the indices of dissimilarity and exposure are employed to measure segregation in Southwark, and these easily understood measures are used as the basis for understanding segregation in this chapter. Finally, network analysis techniques are explored in order to visualise the structure and linkages between different ethnic groups in Southwark.

The data underlying the assessment of segregation must be aggregated in some manner to

areal units; spatially defined, non-overlapping zones. As such, the resultant measure of segregation or exposure is dependent on the size of zones used (Wong, 1997) as a result of a statistical characteristic known as the modifiable areal unit problem (MAUP: Openshaw, 1984). Politically it may be advantageous to report segregation indices at different levels of spatial aggregation, for example when assessing national or regional integration and cohesion of immigrant groups as opposed to local, neighbourhood level instances. Indeed, datasets such as the UK Census of Population are built to allow such enquiries, by disseminating aggregate data within a nested spatial structure that ranges from Output Areas of c.300 people to the nation as a whole. On this basis, and owing to the fact that the Southwark Patient Register is geocoded to the household level, the magnitude of segregation can be assessed across a range of scales, and even independent of explicit areal units by way of Reardon and O'Sullivan's (2004) method. This is a marked improvement on the segregation statistics that can be derived from government data, which are limited to areal units for non-disclosure purposes.

Such neighbourhood levels of aggregation are still large when the concept of 'social distance' (Bogardus, 1933) is considered; social distance attempts to quantify the extent to which people are willing to have others belonging to different ethnicities, or social groupings, as one of their family, friends, neighbours etc. Schelling's (1971) model of residential segregation also demonstrates how local preferential processes, such as a small preference for neighbours with particular social, cultural, linguistic or ethnic characteristics, can over time lead to increasing segregation. However, traditionally measures of segregation do not extend below the level of the wider neighbourhood and in doing so fail to capture finer grain effects, although Friedman's (2011) treatment of proximate neighbours in the US is a notable exception. This chapter presents indices from aggregations of data arising at the household level, and incorporates the building and the street prior to the consideration of the neighbourhood and larger scales. In this way, an understanding of more local segregation effects can be made.

4.2 Ethnicity in Southwark

In order to understand why certain spatial patterns of segregation may exist, it is important to be aware of the historical geography of the area of study. This echoes Simpson's (2004) view that studies should be sensitive to change over time and other confounding factors.

Carter's (2008) work on race, class and social housing in Southwark presents a detailed context for the distribution of ethnic groups in Southwark that makes both for interesting reading, and directly ties in with the ethnic patterns shown in this paper. Carter (2008) shows that ethnicity is a key factor in Southwark politics, and that the pre-eminence of ethnicity as a defining social characteristic in the Borough resulted from the changes in housing policy since 1945 that specifically affected non-middle class residents. Carter illustrates the patterns of residential segregation of minorities in Southwark by mapping the percentage minority population of Southwark by ward for 1971, 1991 and 1998 (2008, p.173-174), showing that the central areas are home to distinctly higher levels of minority population than the north and south of the borough.

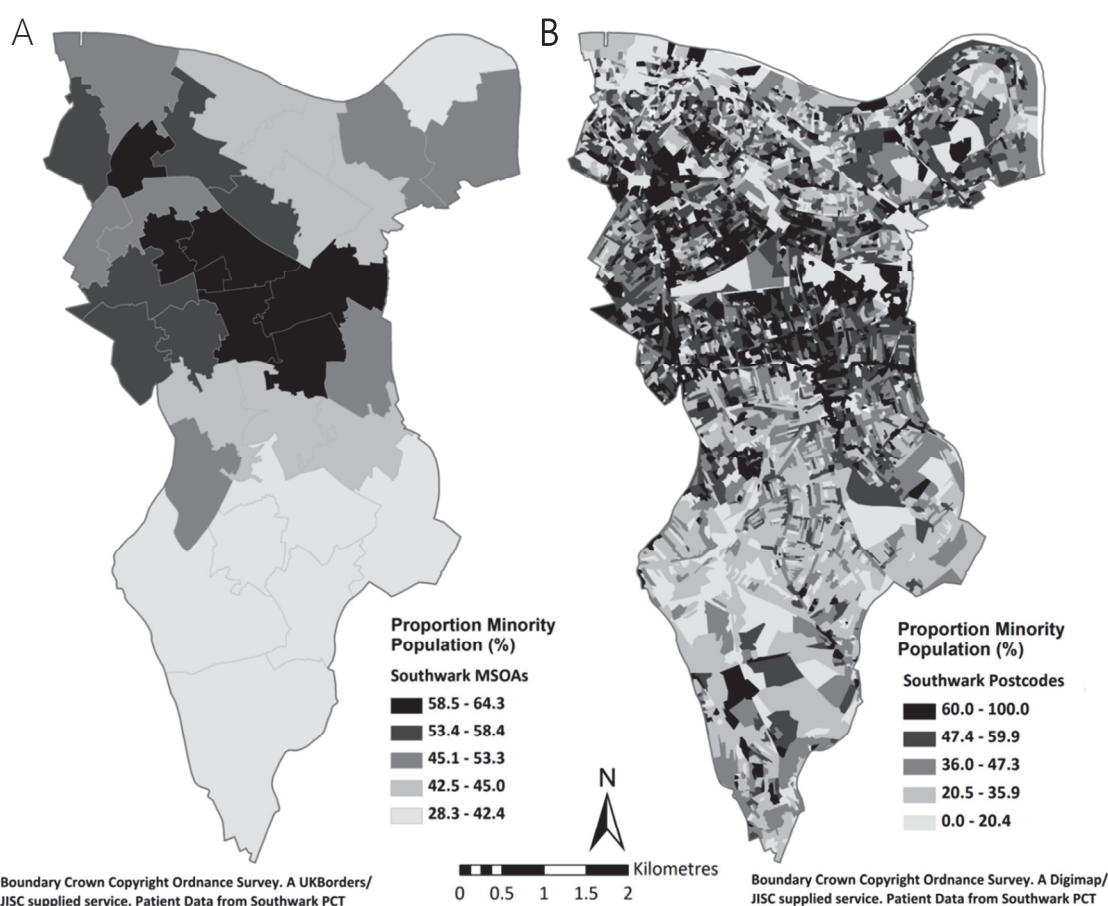


Figure 4.1: Proportion minority population by A) MSOAs and B) postcodes for Southwark 2009.

This can be demonstrated using the Southwark patient register for 2009 (Figure 4.1), although in this case minorities are defined by their surname as not being a member of the 'British' group rather than using the Census defined ethnicity variables. The pattern observed by Carter for wards over 10 years ago is still clearly visible at both MSOA and postcode levels of aggregation. The reasoning behind the apparent concentration of minorities does

not parallel the American experience of ghettoisation, rather as Carter (2008) explains, it is largely the product of chance driven by availability of social housing:

“These divisions largely reflected the historic availability of housing as successive waves of families had been re-housed – the moves of white families into council houses in the north, the arrival of the first wave of Afro-Caribbeans who were forced into owner occupation in Peckham, the rehousing of the next wave of Afro-Caribbeans into less-attractive council housing in the centre of the borough, and finally the arrival of African refugees (who were evenly spread). The spatial locations of these groups provided a basis for the later development of political cleavages.” (Carter, 2008 p. 174)

The Southwark Patient Register data also contains further evidence for more recent migrations from Eastern Europe as a result of the expansion of the European Union in 2004, whose spatial patterning seems largely congruent with the (western) European population of Southwark. Similarly, the East Asian population, who are more recent migrants, seem more spread out than most groups, and live in areas more associated with higher deprivation than the South Asian group who were historically much earlier migrants and who live in the similar areas to the British ethnic group. Whilst Carter (2008) notes that the growth of social housing in Southwark led to less gentrification than was apparent in other boroughs leading up to 1995, regeneration since 2000 in Southwark has been viewed as displacing established social housing tenants in favour of more affluent groups.

The Centre for Urban Policy Studies (CUPS), at the University of Manchester, developed a functional typology of deprived neighbourhoods (Robson et al, 2008; 2009) which gives an insight into the dynamic processes that small areas are undergoing; they identify four types of deprived neighbourhoods: escalators, gentrifiers, isolates and transits. This is effectively an attempt to measure the “connectivity” of an area, it first asks: is there any asymmetry in the people moving into an area, as opposed to moving out? Secondly, focusing on deprivation it considers, if there is an asymmetry, is this likely to have a positive or negative effect? E.g. Are immigrants to a residential area relatively more or less deprived (based on the area they are coming from) than those leaving. The typology operates on household mobility data from the 2001 Census, however, using a more temporally relevant view might be available if the research were to use NHS primary care patient registers. Figure 4.2 shows the CUPS typology as it applies to Southwark. Immediately noticeable is the extent to which Southwark

is deprived, with the vast central tract falling within the 20 % most deprived LSOAs (Lower Super Output Areas, Census dissemination areas of c.1500 people).

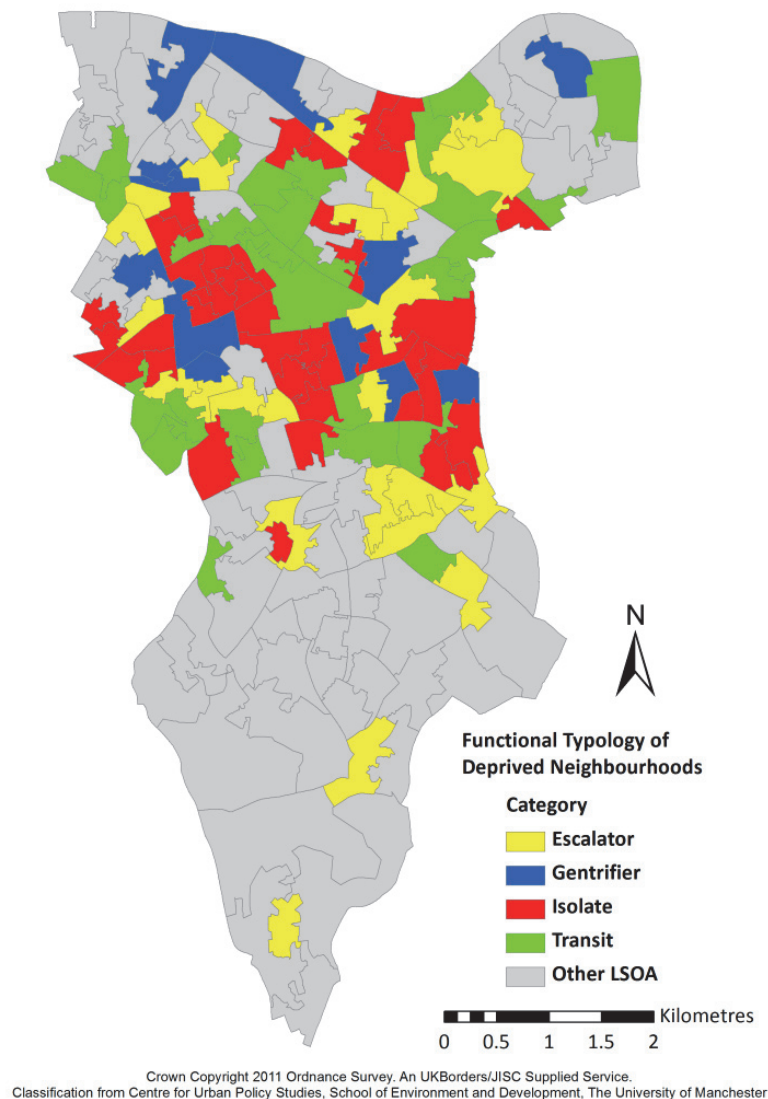


Figure 4.2: Functional Typology of deprived Neighbourhoods for Southwark, London.

The diversity of fortunes of different deprived areas in Southwark is worthy of note: the red 'isolate' areas represent people who are largely trapped at a persistent level of deprivation; the green 'transit' areas represent temporary deprivation, particularly for first-time-buyers who cannot immediately afford to live in less deprived areas; blue areas are subject to gentrification; and yellow areas represent stepping stones from more deprived areas to less deprived areas. All these processes are occurring adjacent to each other in a relatively small area. There are few distinct geographical patterns of be observed in Southwark with respect to the typology, aside from some evidence of local spatial clustering. Robson et al (2008) suggest this is the result of the "pressures of the London housing market" (p.2700) in which

demand for housing, particularly amongst young people, has led to highly mixed patterns which points towards a gradual, and stratified process of gentrification, or transition to better neighbourhoods. This “pockets of gentrification” reading is certainly supported anecdotally within Southwark, however it is unclear how persistent the classification of LSOAs shown in Figure 4.2 will prove to be over time, the classification is based upon data from 2001 and hence may reflect a past reality.

4.3 Contemporary Ethnic Composition in Southwark

4.3.1 Ethnic Population Density

Following the map of population density given in Chapter 3 (Figure 3.3.A) it is possible to disaggregate the ethnic groups and create a view of ethnic residential densities for each defined Onomap group. This is illustrated in Figure 4.3; the bandwidth and cell size for the representation was set consistently for all groups, and was 250m and 25m respectively. The visualisation uses five classes for ease of interpretation, and because the data are not normally distributed, exhibiting a positive skew, the geometric interval method of classification is used. The classes created using the geometric interval classification ensure that each class range has approximately the same number of values in each class, and that range of a class is fairly similar across all classes (Coulson, 1987). The geometric interval method represents a balance between the quantile and equal interval classifications: as such it is also often called the ‘smart quantiles’ method. It is a useful alternative to ‘natural breaks’-style classifications (of which Jenks’ (1977) is most notable), Jenks’ natural breaks aims to present a series of break values that best represent the actual breaks observed in the data as opposed to some arbitrary classificatory scheme (i.e. equal interval). However, it is unclear how to select a number of classes representative of the data in question, which can lead to arbitrary groupings. The data itself (particularly if there are many repeated values) can also artificially create very narrow, or very wide, groupings which may be difficult to usefully interpret. The geometric interval method, in weighing the equal interval and quantile approaches avoid the at times unexpected behaviour of natural breaks classification methods, even in the case of repeated values.

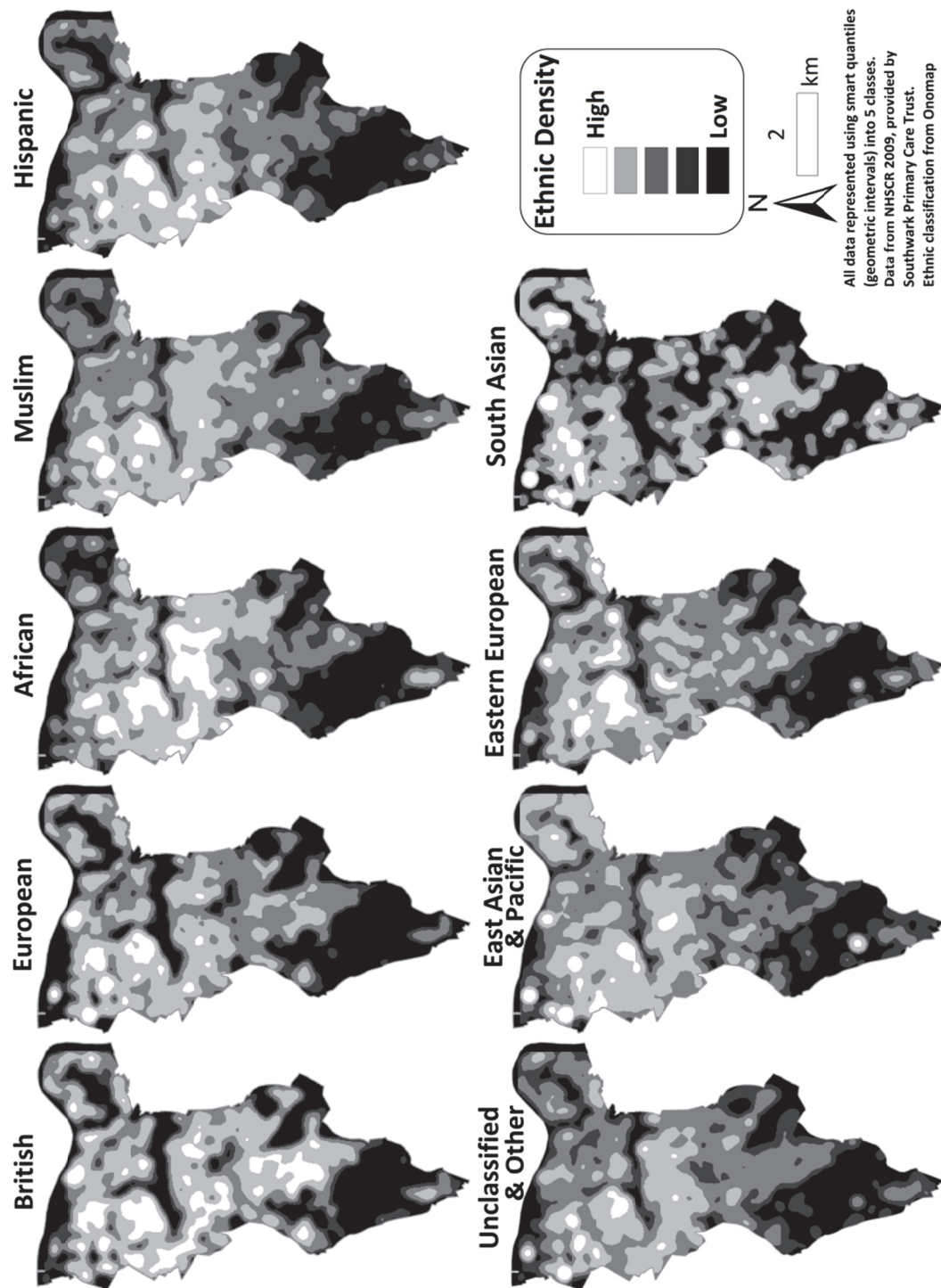


Figure 4.3: Residential density of Onomap-coded Ethnic groups in Southwark. Ordered by population size as per Chapter 2, Table 2.8.

Figure 4.3 makes it clear where the density of any given group is particularly high; however it struggles to identify the extent to which an area of high density is in fact a distinct ethnic cluster. The simplest approach to considering the extent to which a distribution is clustered or not is to use a Location Quotient (LQ), this is an index for comparing a region's share of a phenomenon, or activity, with the share of that phenomenon or activity existing at a more aggregate spatial scale (Burt et al, 2009).

4.3.2 Location Quotients for Studying Ethnicity

Location Quotients are most commonly used to assess concentration of industries in studies of industrial location, and are commonly referred to as a type of economic base analysis. However, their application is far wider than simply industrial research, Winney et al (2011) for instance, used them to study the concentration of regional surnames, whilst they have been used in numerous studies in health geography to uncover patterns of healthcare access and utilisation. The mathematical definition (equation 4.1) in the context of ethnicity is:

$$LQ_i^j = \frac{A_i^j / \sum_{i=1}^n A_i}{B_i^j / \sum_{i=1}^n B_i} \quad (4.1)$$

where the Location Quotient of ethnicity j in area i is equal to the population of ethnicity j in area i over all people in area i , over the total population of people of ethnicity j in the wider region over the total population of that region.

The resultant values can be interpreted thus:

- LQ > 1 Relative concentration of a particular ethnic group in the area compared to the region
- LQ = 1 Share of a particular ethnic group in an area reflects that of the region as a whole
- LQ < 1 Share of a particular ethnic group in an area is lower than that generally observed in the region.

Generally, LQ indices are constructed for existing areal units, but in fact, any set of zones can be constructed within which to calculate the LQ. We could create a square grid of zones for Southwark and count the numbers of each ethnic group that falls within each zone, however, the danger of constructing a regular set of zones over an irregularly distributed population means that there will be varying numbers of people falling in each zone, thus a statistic may be more robust for some zones than others. Further, if the zones are drawn too small, many zones will not have any people in at all, and this will affect the resultant visualisation. One way of dealing with this is to ensure you are using sufficiently large zones,

or to use pre-existing zones; the other way is to create a fine set of zones, such as in a high resolution raster representation, and smooth the discrete distribute of people subject to a local function. Such a method is called kernel density estimation, and it allows a smoothed representation of a discrete phenomenon to be rendered. Having done this for all ethnic groups, so that each small raster cell has a value related to the number of local people of each different ethnicity, the LQ can be calculated to present a continuous field representation of concentration of ethnic groups in Southwark.

In calculating the kernel density surface, it is important to use a consistent bandwidth and cell size across all ethnic groups, however it is not expressly clear what that bandwidth should be. In a sense, the bandwidth is representing the extent of each cell's neighbourhood, and ought to be tied to the extent to which neighbourhood composition changes over space. Further, the value should be small enough to pick out detail, but not so small that it simply highlights existing point locations. Different bandwidths were tried between 100m and 500m with values at the low end appearing undersmoothed, and hence still too discrete, whilst values at the higher end appeared oversmoothed, and hence too generalised. The final value chosen was 250m which presented an effective compromise in terms of the resultant visualisation: the cell size was 25m. Figure 4.4 maps Southwark Onomap ethnic groups by their LQ value, variations over space suggest, in some cases, local population concentrations.

There are distinct differences in the visualisations of LQs when compared to density alone (Fig. 4.3). Whilst the apparent trend for the African population to concentrate locally in the Borough's centre persists, any indication that the British, Eastern European or European groups are significantly concentrated in any one area disappears. Similarly, the spatially heterogeneous distribution of South Asians in Figure 4.3 seems to resolve when LQs are considered, demonstrating a north-south concentration that suggests an under representation of South Asians in the centre of the Borough. Muslim and Hispanic groups mirror the LQ distribution of the African group, whilst East Asian groups demonstrate a northern bias in their distribution that is not readily apparent in their density distribution. The unclassified group is not shown in Figure 4.4, but like the British group reveals very little distinct concentration of population in any place in particular.

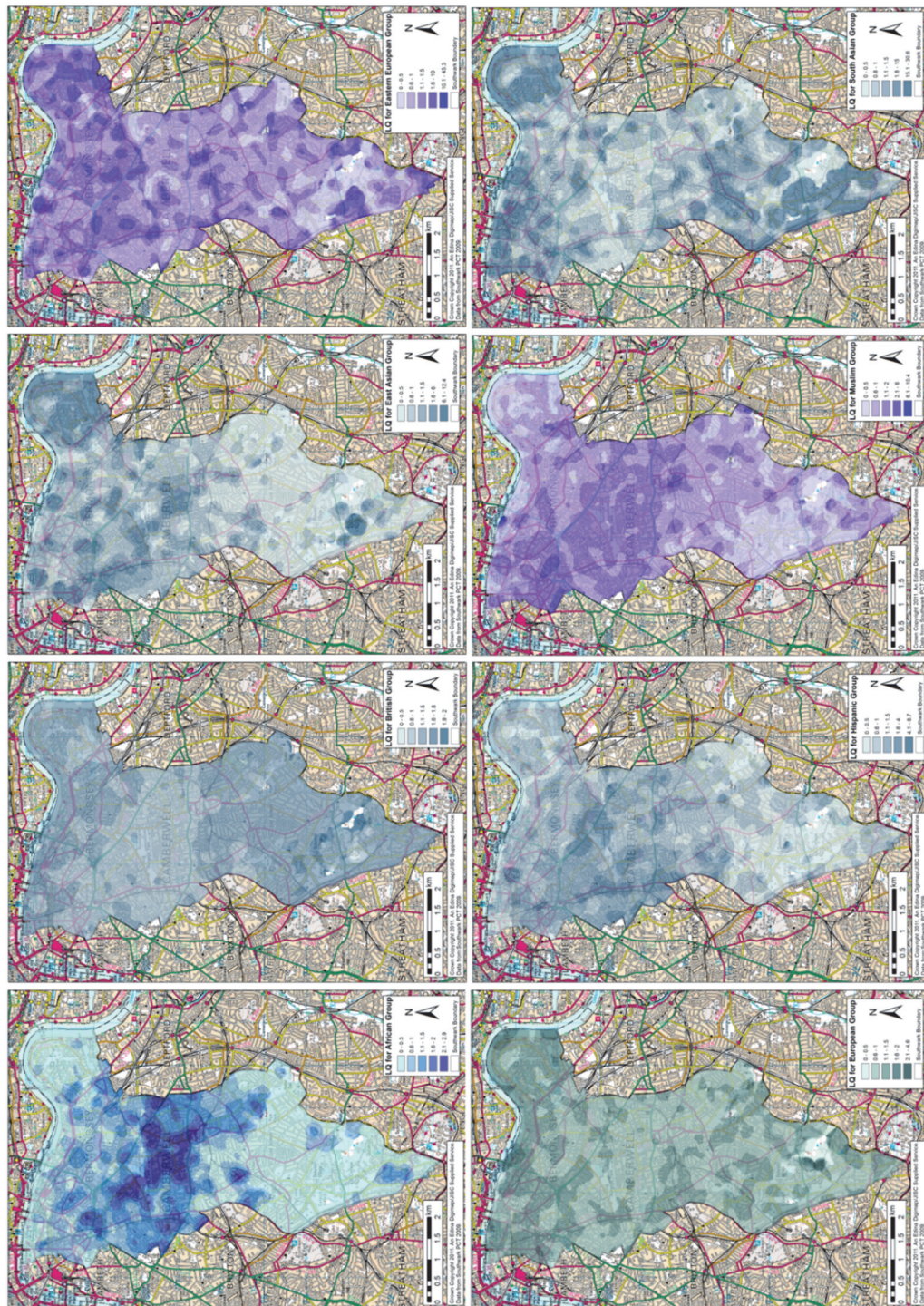


Figure 4.4: IQs for Southwark ethnic groups
 (top left to bottom right): African, British, East Asian, Eastern European, European, Hispanic, Muslim and South Asian.

The fundamental difficulty with the LQ approach is that it does not offer a real window into whether a particular score is significant or not, instead this has to be judged from the context specific to each study. It is also important to note that patterns of spatial concentration of ethnic groups is a process which is in part causal and in part random, as suggested in the allocation of social housing in Southwark by Carter (2008), and more broadly by Kawachi and Berkman (2003), in this sense concentrations of some ethnic groups may be unintentional. Nonetheless, the spatial distribution of some groups will have an effect on their ability to access services and could raise social justice issues as discussed by Harvey (1973), Smith (1977) or Fainstein (2005). Some researchers have attempted to infer significance from LQ scores (O'Donoghue and Gleave, 2004; Moineddin et al, 2003), whilst others attempt to reengineer the index in order to derive statistics for significant localisations of a group or of an industry (Duranton and Overman, 2005); all such approaches incur a penalty of increasing complexity, moving away from the simplicity of execution and conceptualisation which is the main virtue of the standard LQ.

4.3.3 Assessing Spatial Diversity in Ethnicity

Visualisation of LQs as in Figure 4.4 can present an interesting view for each ethnic group, however it is difficult to assess what this means in practice – society is a composite phenomenon, not something that can, in an academic sense, be broken apart easily, and so a measure of the diversity of an area as a whole is as powerful as the atomistic understanding of whether a particular group concentrates there. It is possible to bring together an understanding of the diversity, or evenness, of the distribution of a set of different groups within an area as a geographic visualisation. Reardon and O'Sullivan (2004) introduce two measures in their set of approaches to spatial segregation: spatial entropy and relative diversity, which captures a value of evenness, or (conversely) diversity over space. Spatially weighted entropy is given by equation 4.2:

$$\tilde{E}_p = - \sum_{m=1}^M (\tilde{\pi}_{pm}) \log_M (\tilde{\pi}_{pm}) \quad (4.2)$$

This equation (from Reardon and O'Sullivan, 2004 p. 139) describes the entropy, or evenness, of a distribution for each cell in a raster image as previously for LQ. π indicates the proportion of people of a particular group m in area p .

In this case the value of each raster cell is defined by a kernel relationship with other local cells. The spatial segregation measures were computed in Python using tools in the SciPy

package rather than in ESRI's ArcGIS, and so the chosen kernel type is Gaussian rather than Epanechnikov as in the previous chapter. The key difference between these two kernels is that the Gaussian kernel estimates a cell value based upon all cells, as the normal distribution is asymptotic to zero – although depending on the specified bandwidth distant cells will only contribute a negligible amount to a resultant cell value. This is discussed further in Chapter 6.

The concept of entropy in this case stems from Claude Shannon's articulation of "Information Theory", however as Batty (1974) notes its articulation can vary substantially across, and even within, domains of "intellectual endeavour". Shannon's derivation relates to the amount of information contained within a probability distribution, but as a possibly apocryphal story suggests it was called entropy by John Von Neumann in a discussion with Shannon:

"'Why don't you call it entropy', von Neumann suggested. 'In the first place, a mathematical development very much like yours already exists in Boltzmann's statistical mechanics, and in the second place, no one understands entropy very well, so in any discussion you will be in a position of advantage'". (Avery, 2003 p.81)

Batty (1974) meticulously dissects the concept of entropy mathematically, however for the purpose of its usage here, the amount of entropy in a probability distribution can also be thought of as that distribution's information content. The value of information can be seen in terms of the information gained by a given event occurring, in which entropy is maximised in a system that is entirely unpredictable in terms of the events occurring. Therefore, there is potentially less entropy to be gained from a recent African immigrant choosing to live in an area of high African concentration, than an area of low African concentration – because our prior expectation is that the African immigrant will seek out a similar residential community to that to which he is accustomed. In a situation in which there is a mixing of different groups, the amount of entropy increases as pre-assigning a new member becomes more and more uncertain – less predictable – until such a point that the distribution of groups is even, making assignation of any person to any particular group equally likely, hence entropy is maximised. It is for this reason that entropy indices are seen as a measure of evenness, because the highest assignable value indicates a situation of complete evenness (maximum entropy), whereas low values indicate a lack of evenness, and potentially dominance by one or a few groups.

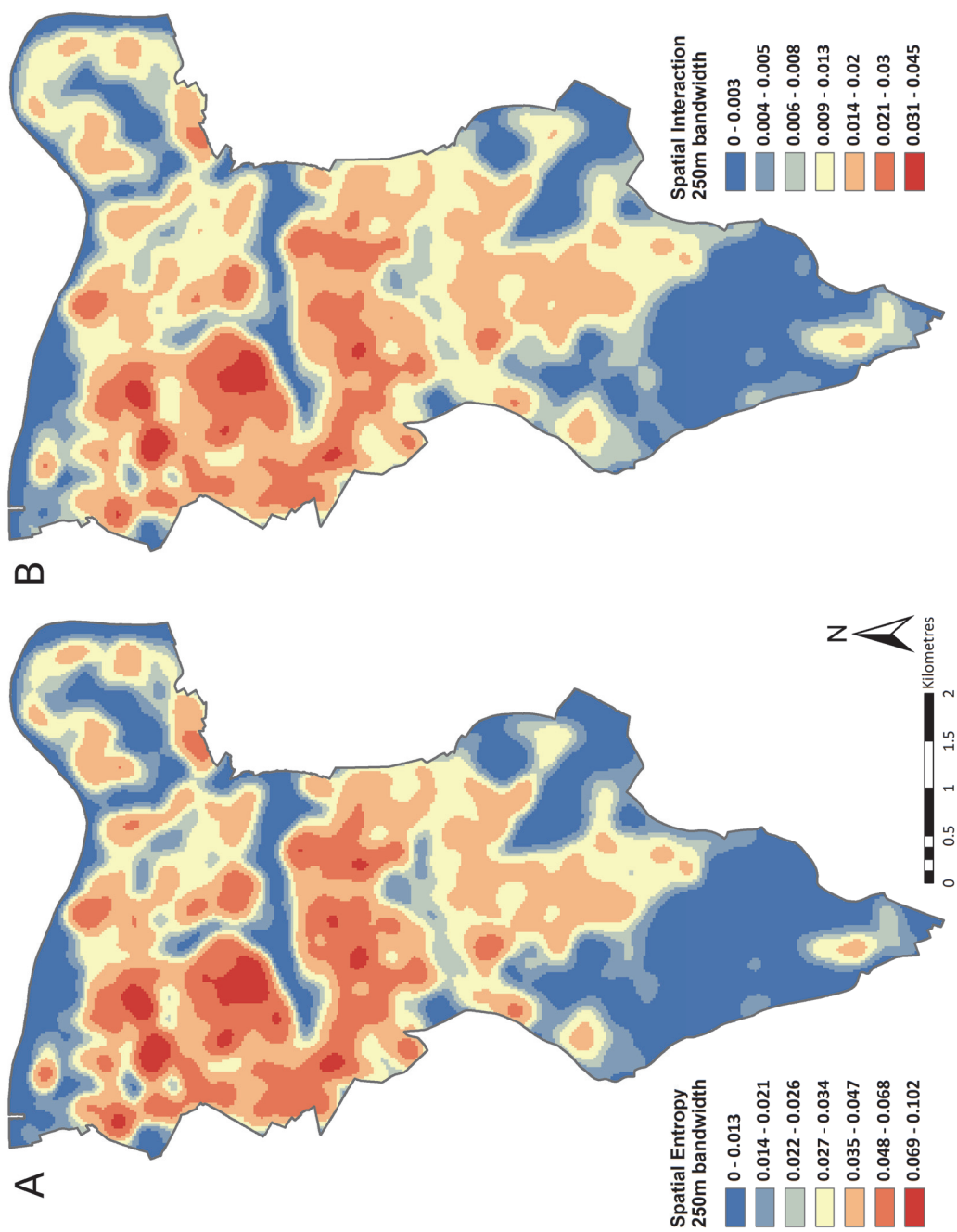


Figure 4.5 Views of Spatial Entropy (A) and Spatial Interaction (B) for Southwark based upon Onomap derived ethnic group distributions.

The relative diversity index defined by Reardon and O’Sullivan (2004) employs a spatially-weighted interaction index, which can also be employed as a continuous surface visualisation of how diverse an area is.

The spatially-weighted interaction index is given by equation 4.3 (from Reardon and O’Sullivan, 2004 p. 140):

$$\tilde{I}_p = \sum_{m=1}^M (\tilde{\pi}_{pm})(1 - \tilde{\pi}_{pm}) \quad (4.3)$$

Here the spatial interaction in an area p is given by the sum for all ethnic groups m of the product of the proportion of each ethnic group in a given area p and 1 minus that value. The specification of p is the same as for spatial entropy and for the LQ above, using a kernel density-based smoothing technique with a Gaussian kernel.

Figures 4.5 A and B show a view of spatial entropy, and spatial interaction respectively for Southwark. Like the LQ, a suitable bandwidth had to be derived under the constraint that it again ought to represent some aspect of the propensity to, or rate at which, individuals form larger communities, consistent with avoiding over- or under- smoothing of the population data. The bandwidth used is the same 250m value as for LQs, with a 25m cell size. Both views of diversity in Southwark are largely consistent: the areas of highest diversity, or entropy, are the north-central areas where the most Muslim and African population are to be found alongside British, European and other less concentrated groups.

4.3.4 Traditional Indices of Segregation for Southwark

Calculating traditional indices of segregation is straightforward, albeit predicated upon data aggregation at some pre-specified areal level. Whilst Reardon and O’Sullivan’s (2005) point pattern-based indices are available for use, they are by no means as widely used as areal indices, further they are harder to implement, and are not directly comparable to the indices calculated in this section for the given areal geographies. In addition, any valid implementation of a point-pattern based indicator of spatial segregation would require a significant theoretical investment into defining neighbourhoods through the choice and parameterisation of the spatial weights matrix. Such an attempt would be useful, and valuable research, but is beyond the scope of this Chapter. On this basis point pattern-based indices of segregation are not considered.

Using the household geocoded Southwark Patient Register, the data have been aggregated into three census level areal units: MSOAs, LSOAs and OAs, postcodes, and the two derived aggregations of building and household. Summary statistics for these aggregations are shown in Table 4.1.

Aggregation	Count	Mean Population	Standard Deviation	Lower Quartile	Upper Quartile
MSOA	33	9857	1275	8873	10553
LSOA	165	1971	345	1765	2190
OA	844	384	139	299	443
Postcode	4461	65	80	15	92
Building	43106	7	23	2	7
Household	89669	3	6	1	4

Table 4.1: Aggregation Characteristics for Southwark

The data in Table 4.1 suggest an increasingly skewed distribution, in which a lengthening tail is evident from OAs onwards. The small numbers of people per building and per household may suggest some uncertainty with regard to the statistical robustness of the indices calculated. In the UK, segregation indices could only realistically be calculated for a population using the census OAs, or coarser aggregations, for data pertaining to the most recent (2001) Census. In a borough which has a high population churn, as Southwark does, the population may have changed greatly in the intervening time. As has been suggested, the Southwark Patient Register offers one of the only near-real time accounts of population composition for Southwark, and the NHSCR does so for England as a whole. Therefore, the patient register, extracted in mid-2009, offers a much more contemporary insight into segregation than can be gleaned from the census. Moreover, the level of disaggregation of the patient register allows a far more detailed appreciation of segregation, indeed it allows an insight into whether populations that mix on a neighbourhood basis also mix in the same street (for which postcode is an approximation) or in the same building. This finer scale of analysis cuts closer to the idea of social distance discussed earlier. Finally, the application of Onomap to patient names allows for the segregation profiling of groups that are not present in the Census's ethnicity classification. The white population can be broken down to investigate the potentially differing trajectories of East European migrants, as opposed to West European, offering some context to the ongoing effects of EU expansion, for instance.

Two straightforward measures of segregation are used initially, the index of dissimilarity and the index of interaction. Both of these are computed for the previously identified ethnic

groups in Southwark at the specified levels of spatial aggregation. The indices are given by equations 4.4 (index of dissimilarity) and 4.5 (index of interaction or exposure, here an index of isolation as it measures the likelihood of someone of a given ethnicity meeting someone of the same ethnicity).

$$D = 0.5 \sum_{i=1}^N \left| \frac{x_i}{X} - \frac{y_i}{Y} \right| \quad (4.4)$$

$${}_xP_x^* = \sum_{i=1}^N \left(\frac{x_i}{X} \right) \left(\frac{x_i}{t_i} \right) \quad (4.5)$$

Where:

x_i = Population of a given ethnic group x in area i

X = Total population of ethnic group x

y_i = Population of all other ethnic groups in i

Y = Total population of all other ethnic groups

t_i = Total population of area i

The index of dissimilarity is a measure of evenness, and gives an idea as to the extent that the distribution of one group would have to be changed in order to match the distribution of another. A value of 0 indicates that no change would be required, hence the two groups are identical, and a value of 1 indicates the opposite, that the two groups are entirely dissimilar. By comparison, the index of interaction (or isolation) is a measure of the likelihood that someone from one ethnic group will meet someone of a different (or the same) ethnic group. It also falls between 0 and 1, however it is affected by group size. In this case the indices measure dissimilarity, or isolation, of one group relative to all other ethnic groups: however the indices could also be calculated with reference to a majority group (in this case it would be British). Using a majority group as a reference, however, would mean not calculating a score for the British group, and in some areas, such as those where a high concentration of minority ethnic groups are observed, scores for British groups might be interesting as they could feasibly be in a minority in some areas. These two indices are demonstrated for Southwark in Figures 4.6 and 4.7.

Both Figures 4.6 and 4.7 demonstrate that as the level of spatial aggregation decreases, the dissimilarity between, or isolation of, different ethnic groups generally increases. This is to be expected, what is more interesting in these two graphs is how the level of dissimilarity or isolation varies across different spatial scales. For instance, in Figure 4.6, the African group goes from having the most dissimilar distribution at the MSOA and LSOA level to the

median most dissimilar distribution at the household scale. This occurs as a result of the South and East Asian, Eastern European and Hispanic groups becoming increasingly dissimilar from other groups at levels finer than the OA. Most notable is the Eastern European group whose dissimilarity rises after the LSOA level of aggregation and which has the greatest increase in dissimilarity of any group across all levels of spatial aggregation.

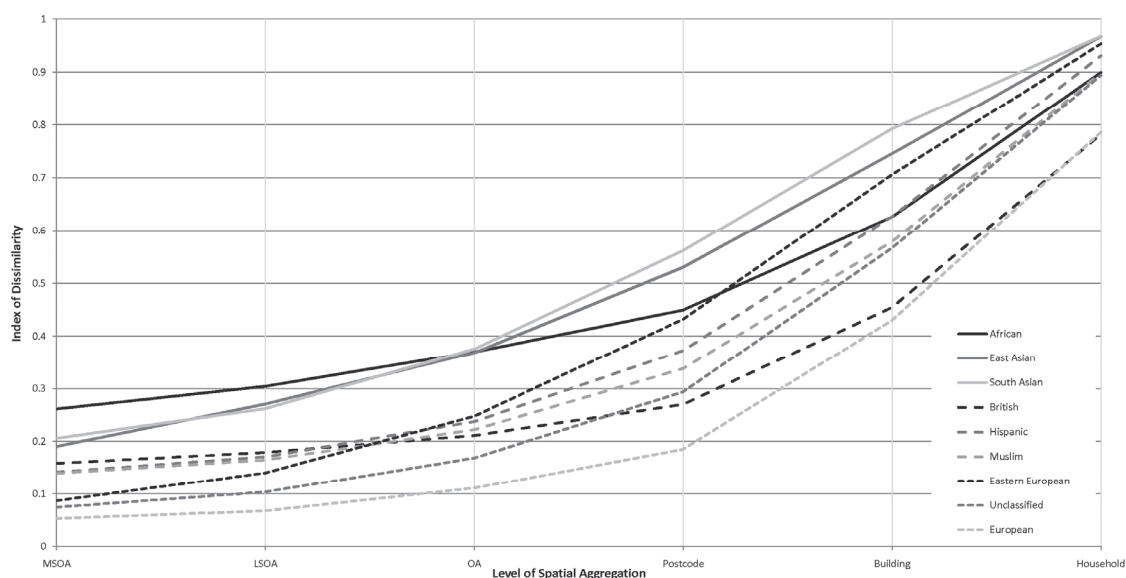


Figure 4.6: index of Dissimilarity (given ethnic group against all other groups) at differing levels of spatial aggregation for Southwark.

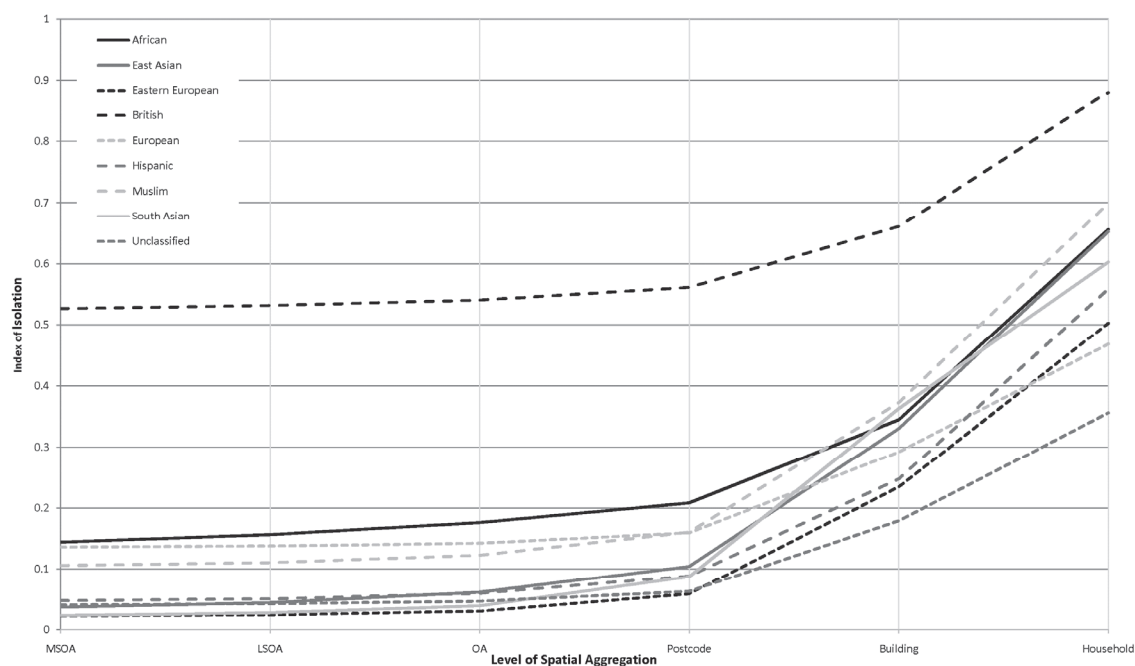


Figure 4.7: Index of Isolation (likelihood of a given ethnic meeting someone of the same ethnicity) at differing levels of spatial aggregation for Southwark.

There are similar trends in Figure 4.7: in this case the index relates to the likelihood of meeting, at random, someone from the same ethnic group within the defined spatial unit of inquiry. Thus someone from the British group has a much greater chance of meeting other British group members simply because there are more British group representatives than any other ethnic group in Southwark. In all cases however, the gap between the British and other ethnic groups decreases across the different spatial scales: that is; a British individual has a higher likelihood of meeting another British member within their postcode, building or household than in their MSOA or LSOA, however all other ethnic groups (relative to the British group) have an even higher chance of meeting someone of their ethnicity in their postcode, building or household than in their MSOA or LSOA. This is particularly true for East and South Asians, but also for African and Muslim groups who now seem more segregated in their postcode, building or household than they do unevenly distributed (dissimilar). The European group is amongst the least isolated, despite being the second most numerous group, across all spatial scales. In both cases the unclassified/other group is amongst the least isolated and least dissimilar, however this group is a catch all group reflecting people with names that could not be coded to an ethnic, cultural or linguistic class by Onomap, thus it is likely to comprise of a mixing of a number of, particularly minority, groups for whom naming practices are less well known.

4.3.5 Summary

This section has demonstrated that there exists a generally identifiable pattern of segregation and of ethnic mixing in Southwark, and highlights the use of several techniques for measuring and describing this pattern. Using the Southwark patient register presents a hitherto unobtainable insight into patterns of segregation across small units, and demonstrates that patterns of segregation actually change when aggregations below the neighbourhood level (OA) are considered. This has implications for policy, if people actually exhibit expressly different behaviours at more local scales than can be investigated using government statistics, then community-level interventions aimed at cohesion or capacity building may well be being misjudged and rendered ineffective. This could be further improved in the future by exploring any differences introduced by considering the point pattern interpretation of segregation pertaining to Southwark.

In the next section, a set of graphical techniques, based upon seeing ethnic segregation as a graph, are investigated. It is suggested that such methods provide a useful visual aid to

interpreting segregation in an area, and also serve to highlight the general structure of dissimilarity, or interaction between different ethnic groups.

4.4 Graph Representation of Ethnic Segregation

4.4.1 The Basis for Graphs: Pairwise Measures of Segregation

A graph is an abstract representation of a set of features, called nodes, which are connected (or not) by links, called edges (de Smith et al, 2009). In GIS, graph representations are commonly used to represent physical road networks; a road junction is a node, and the actual roadway is represented as an edge. If a vehicle were being routed, the nodes in the network allow for different route choices to be made, opening up the complete navigation of a given network, and the edges carry a record of length, or time taken for traversal, in order that metrics such as “shortest path” or “least cost path” can be calculated. A straightforward graph is undirected, meaning that edges can be navigated from either end, however a network can be constrained so that edges can only be navigated in one direction, creating a digraph, as with representing one-way roads. Graphs are commonly also used to represent far less tangible networks, such as the flows of money between financial centres, or the structure of human resource flows within an organisation. Manuel Castells has long been associated with the conceptualisation of network approaches to space in Geography and Sociology, bringing the idea of a “network society” and a “space of flows” (1996) to a wide audience. In this section a method for representing ethnic structure as a graph is investigated, and different views derived from this are developed. Although these graphs will be constructed for varying levels of aggregation, they are otherwise inherently aspatial representations.

Mateos et al (2011) demonstrate the use of network analysis in understanding forename and surname naming-networks, and show how a graph theoretic approach can be used to develop a taxonomy of cultural, ethnic or linguistic origin based upon names. Such graph theoretic approaches can be used to further consider segregation. If each ethnic group previously defined is thought of as each one of nine possible nodes, then the dissimilarity, or interaction, between any two ethnicities can be given by the weight of the edge joining two nodes. Because the chances of interaction, or the similarity, between any two ethnic groups is contingent upon their particular spatial arrangement, then the resultant edge weights for

the complete graph will vary. Different methods for manipulating the complete graph, such as removing edges that represent the highest dissimilarity, or least interaction, will allow the strongest associations between ethnic groups to remain, and reveal a general structure of relationships between ethnic groups. It is just as simple to calculate the value of a segregation index for two ethnicities, as it is between one ethnicity and all others: in principle it simply requires the application of either equation 4.4 or 4.5, using a second ethnicity instead of the value for all other ethnicities. However, because the index of isolation/interaction (equation 4.5) is based on the absolute number of people in a given area, it will always report that the most likely other ethnic group that a member of any group might encounter is British, in a pairwise context it is more interesting to ask which groups would be more likely to interact irrespective of absolute group size. This can be achieved by normalising the isolation/interaction index (Bell, 1954) as in equation 4.6.

$$I_2 = \frac{\sum_i \frac{x_i}{X} \cdot \frac{y_i}{T}}{\frac{Y}{T}} \quad (4.6)$$

In which the denominator is the proportion of the second ethnic group in the total population.

If all pairwise dissimilarities are calculated using equation 4.4, a triangular matrix can be generated, as shown by Table 4.2. The matrix is symmetrical about the principal diagonal: the same value is returned for the dissimilarity between one ethnicity and other, and vice versa. The data are presented for the MSOA level of aggregation, the coarsest aggregation under consideration.

<i>Individual Ethnicity</i>	African	East Asian	E. European	British	European	Hispanic	Muslim	South Asian	Other
African	0.0								
East Asian	0.25	0.0							
E. European	0.26	0.17	0.0						
British	0.30	0.24	0.11	0.0					
European	0.27	0.18	0.08	0.08	0.0				
Hispanic	0.17	0.19	0.15	0.21	0.17	0.0			
Muslim	0.16	0.16	0.16	0.20	0.15	0.15	0.0		
South Asian	0.39	0.26	0.20	0.18	0.16	0.29	0.27	0.0	
Other	0.19	0.15	0.11	0.14	0.09	0.10	0.08	0.23	0.0

Table 4.2: Pair-wise Index of Dissimilarity for MSOAs in Southwark (shown to 2 decimal places)

Table 4.2 illustrates the relative evenness in the distribution of pairs of ethnic groups, albeit with several noteworthy exceptions: for instance that the African group is more similar to the Muslim and Hispanic groups makes some cultural sense, whilst being least similar to the British, South Asian and European groups reinforces the patterns shown in Figure 4.4. However, Table 4.2 requires a lot of time for interpretation, and a significant effort to consider all 36 ethnic group pairs (45 including same ethnicity pairs), notwithstanding that similar tables can be created for all of the levels of aggregation under consideration. In practice, matrices are the tabular representation of graphs, and it is straightforward to transform the tabular representation in Table 4.2 to a graph representation, as demonstrated by Figure 4.8. The graph displays an edge for each link, and as each node is connected to every other node, the graph is known as a “complete graph”. The graph edges are displayed as having different thicknesses according to their level of dissimilarity, the continuous dissimilarity values are classified into 4 classes using the natural breaks algorithm (Jenks, 1977). The resultant classes are defined by apparent breaks in the distribution of data values, the process is one of optimisation in which the variance within classes is minimised and the variance between classes is maximised (Coulson, 1987). However, even if the edges of the graph are classified according to weight (dissimilarity), and an attempt is made to order the location of nodes as in Figure 4.8, the outcome is difficult to interpret with ease.

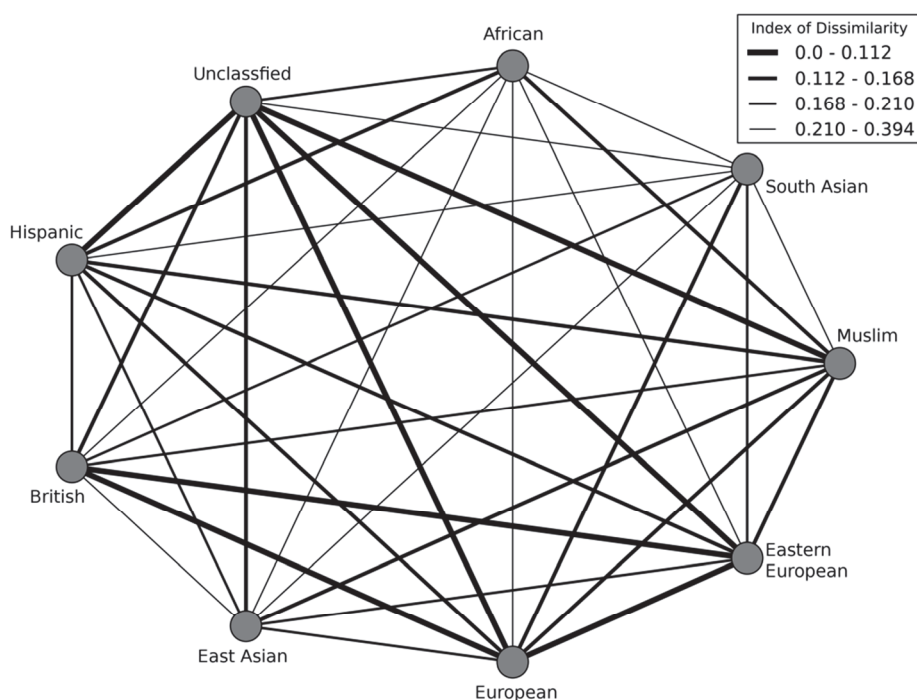


Figure 4.8: Pairwise index of dissimilarity for ethnic groups in Southwark MSOAs, classified by natural breaks

Rather than classify edges by thickness, as in Figure 4.8, it might also make sense to colour the edges subject to a colour ramp: this could capture the continuous nature of the data better than a classification approach in which information is lost. The continuous colour ramp approach is demonstrated in Figure 4.9. In both cases, the relative dissimilarity of the African group from all other groups is highlighted, in Figure 4.8 the African group is connected by the thinnest edges, and in Figure 4.9 the most red-hued edges. In addition, the similarity of some groups is demonstrated, such as the British, European, Eastern European triangle, or the Unclassified group which is quite well connected to several groups hinting at the diverse nature of those patients who could not be classified using Onomap.

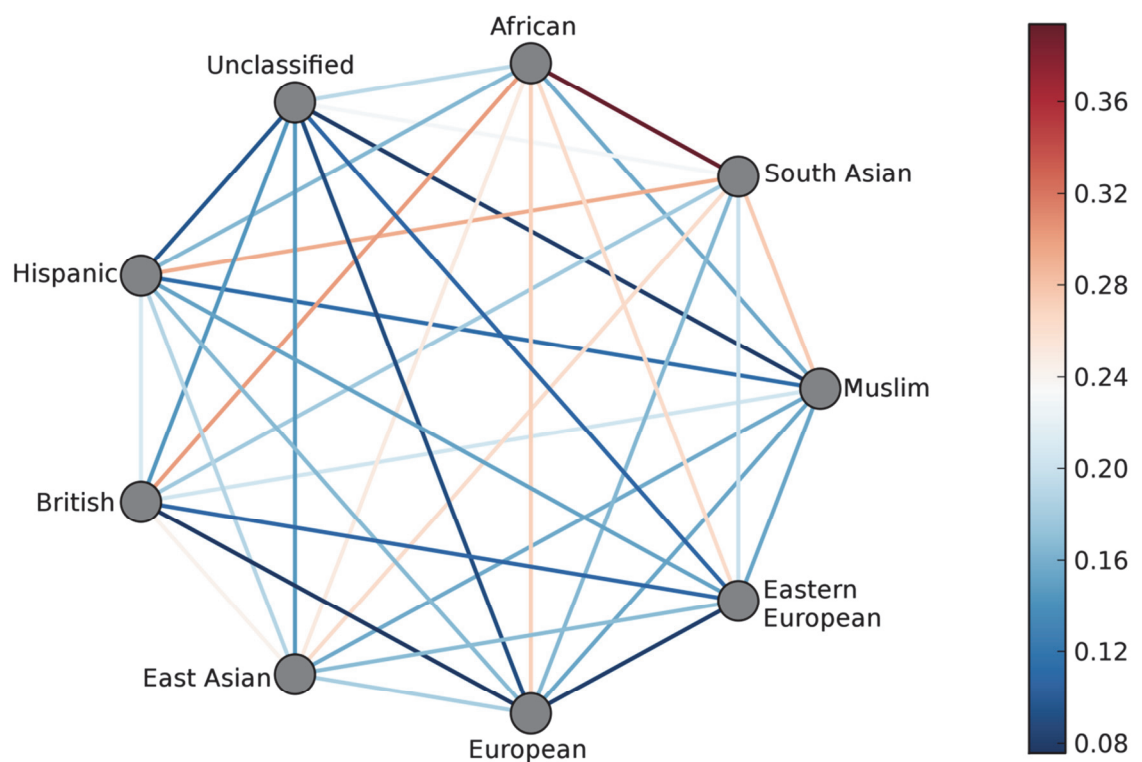


Figure 4.9: Pairwise index of dissimilarity for ethnic groups in Southwark MSOAs, using colour ramp visualisation

The same can be achieved for the normalised interaction index (equation 4.6), however unlike the dissimilarity index in which high values denote high dissimilarity, in the case of Figure 4.10 the higher the value for the normalised interaction index, the higher the chance of interaction between two groups (adjusted for group size). Similar patterns emerge, as are present in the dissimilarity index results (Figure 4.9) however, the relative dissimilarity of the African group from most other groups is replaced by high likelihoods of interaction with, in particular, the Muslim and Hispanic groups. It does seem to be the case that the dissimilarity

and interaction indices are capturing different aspects of segregation in Southwark, which validates their consideration.

In these examples (Figures 4.8, 4.9 and 4.10) the areal geography used is MSOA, however if all available geographies are considered (as in Figures 4.6 and 4.7) then the level of visual complexity is greatly increased. The visualisation could be presented as small multiples (Tufté, 1983), however, leaving all the graphs complete (i.e. possessing all possible edges) increases the number of edges to interpret from 36 for a single graph to 216 edges over 6 graphs. Therefore, either a way of simplifying the graphs to make interpretation of a small multiple easier, or a method of presenting all graphs in a single visualisation, is required. As has been suggested previously, there may be important changes to the level of segregation evident in Southwark at different areal aggregations. In the next sections, simplification by graph pruning and minimum spanning tree algorithms are investigated for the use of small multiples, and multi-dimensional scaling (MDS) is considered as a way of introducing additional ways of creating networks from the graph data.

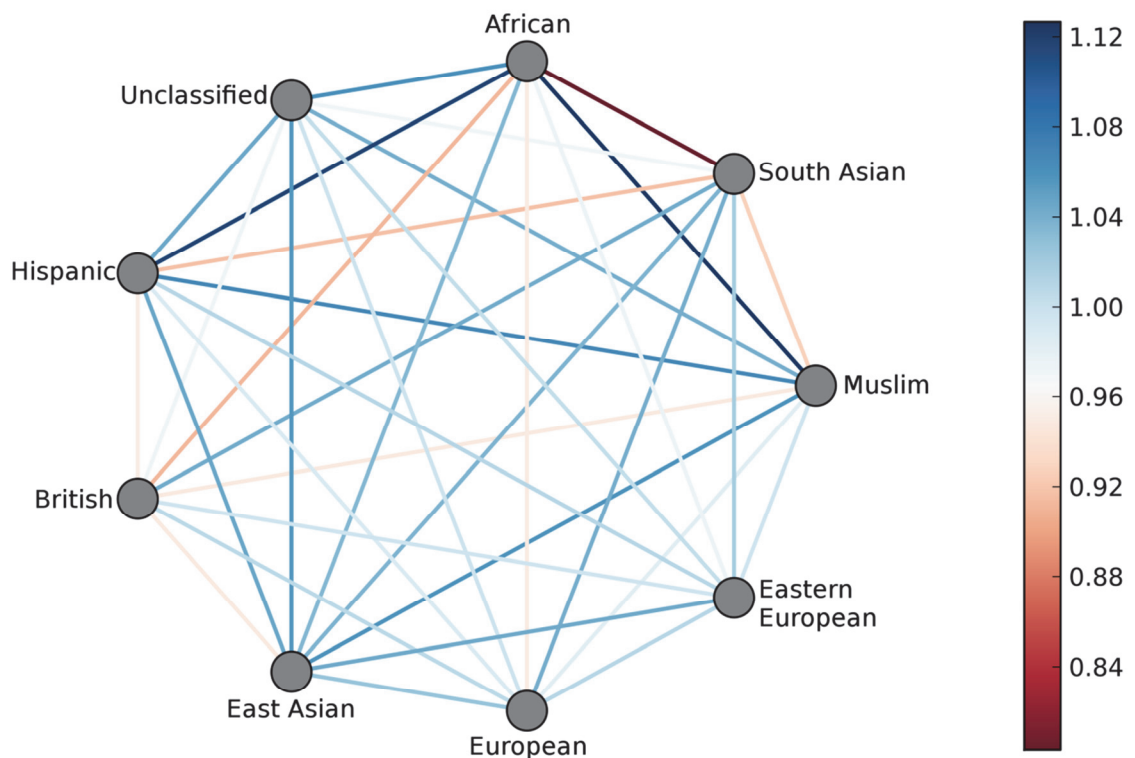


Figure 4.10: Pairwise normalised index of interaction for ethnic groups in Southwark MSOAs, using colour ramp visualisation

4.4.2 Simplifying the Complete Ethnicity Graph

The most straightforward way of simplifying the ethnicity graph is to progressively remove the edges which denote either: most dissimilarity, or, least interaction, between ethnic group pairs. The full set of removals possible is shown for MSOAs in Figure 4.11, it is of interest to note the stage during the process in which an ethnic group loses its edges. In Figure 4.11, the African group is the first to lose multiple edges, but it is the South Asian group that loses all its edges first, suggesting that in some sense it is the ethnic group that is most dissimilar from all others. The African group follows the South Asian group closely in terms of edge loss, with East Asian, Hispanic, Eastern European, and Muslim and Unclassified groups subsequently losing their edges, the British and European groups are the most similar in the Southwark context.

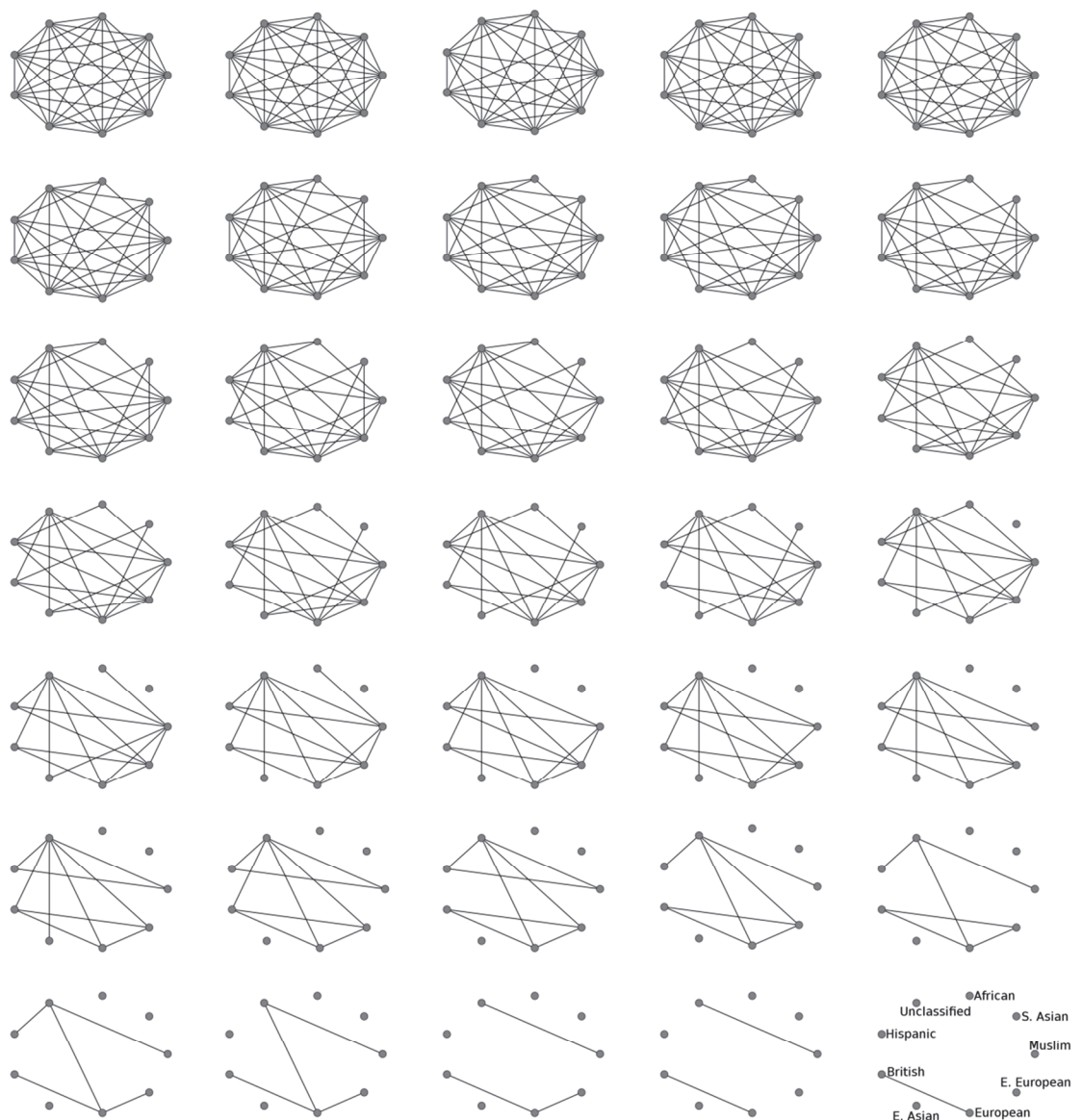


Figure 4.11: Small multiple showing progressive removal of most dissimilar edges linking ethnic groups in Southwark.

Removing graph edges, as in Figure 4.11, provides a basis for creating a simplified representation of segregation; however, visualising the sequential set of edge removals in full is not ideal. Instead, a set number of removals, representative of the most similar ethnic groups, could be made to produce a single simplified graph. It might appear useful to pick the highest number of removals so that each node (ethnic group) has at least 1 edge, however this is somewhat arbitrary and may make little sense in terms of the distribution of dissimilarity values. In this sense it may be more appropriate to use statistical techniques that account for the distribution of data. One such technique is the application of outlier analysis methods which can be used to exclude extreme outliers over a defined size from the data distribution. However, most outlier analysis routines are based on normally distributed data, this is problematic in the case of the distribution of dissimilarities or interaction measurements as there is no prior reason to expect a normal distribution, and with only 36 data points, there are not really enough to confirm or deny the presence of a normal distribution.

Previously, the Jenks natural breaks optimisation method for defining class intervals has been used (Figure 4.8) which works by statistical detection of the best arrangement of data values into a pre-specified number of classes. It is possible to use this to divide edge data into distinct classes, and then omit classes that group high data values, but again this is an arbitrary act, and one that relies on prespecifying a number of classes. If two classes are used, creating a binary classification, then the African and South Asian groups are immediately excluded from the resultant graph, effectively limiting the usefulness of the visualisation for these groups. Moreover, the complexity of the resultant visualisation is still quite high. Therefore, without knowledge of an externally derived threshold value with which to prune the graph, such straightforward techniques for simplifying the ethnic dissimilarity or interaction graphs are ineffective. On this basis using the graph's minimum spanning tree is considered in the next section.

4.4.3 Minimum Spanning Trees

For a connected, undirected graph, such as in Figures 4.8-10, a spanning tree is a subgraph that connects all of the nodes together without forming any cycles ("loops"). Thus, a minimum spanning tree (MST) is the spanning tree that connects all nodes together with the least possible weight (de Smith et al, 2009 p.416). In this case, nodes are ethnic groups, and the weight of lines is represented by the level of segregation between groups. In this way,

the structure of the graph gives a simplified insight into the structure of the segregation of ethnic groups in an area at a given scale of spatial aggregation. As each edge in the graph has a different weight to any other edge (n.b. Table 4.2 is summarised to 2 decimal places, which is why some pairs appear to have equivalent values), there will always be only one possible minimum spanning tree, in the unlikely event that 2 edges have the same weight there is a possibility that more than 1 MST may be generated, although that is not the case for any of the Southwark Patient Register data at any level of aggregation studied.

The straightforward MST can be derived from any graph based upon the index of dissimilarity, this is because low edge weights represent more similarity between nodes, thus the MST represents cultural, ethnic or linguistic groups which are most similar, subject to the imposed tree-like structure. However, in a normalised interaction index graph, low edge weights imply greater segregation, if the desire is to represent pairs of nodes with greater interaction between them a maximum spanning tree must be used instead. The maximum spanning tree is the opposite of the minimum spanning tree, creating a graph with the smallest set of highest weight edges that join all the nodes together. Eppstein (1999) shows that the maximum spanning tree can be created using a minimum spanning tree algorithm with a dataset in which edge weights have been negated. The minimum spanning tree is computed using the NetworkX package (Hagberg et al, 2008) in the python programming language, which implements Kruskal's algorithm (1956).

Having computed a minimum spanning tree, it is also useful to change the visualisation layout from the circular form shown previously for complete graphs, to something that can provide additional context for a MST. Such a layout can be achieved by employing the Fruchterman-Reingold force-directed algorithm (Fruchterman and Reingold, 1991), often seen as analogous to a system of springs. The Fruchterman-Reingold algorithm creates a graph layout by supposing that nodes have forces acting on each other, attractive forces between adjacent vertices and repulsive forces between all other pairs, these forces are subject to the edge weight. The forces in the system act on each other for a specified number of iterations until the system has reached a "minimum energy state" or all iterations have been completed. The result is a graph that should obey two principles: "1. Vertices connected by an edge should be drawn near each other. 2. Vertices should not be drawn *too* close to each other" (Fruchterman and Reingold, 1991 p. 1131). In addition to this layout, the colouring of edges as per Figures 4.9 and 4.10 is used to further highlight the

magnitude of dissimilarities or interactions of the edges in the MST. This is useful, as the MST ensures a connected graph- there are no disconnected nodes as was happening with South Asian and African groups when simply pruning the graph as per Figure 4.11. The results of the MST method, for dissimilarities and normalised interaction are presented in Figures 4.12 and 4.13.

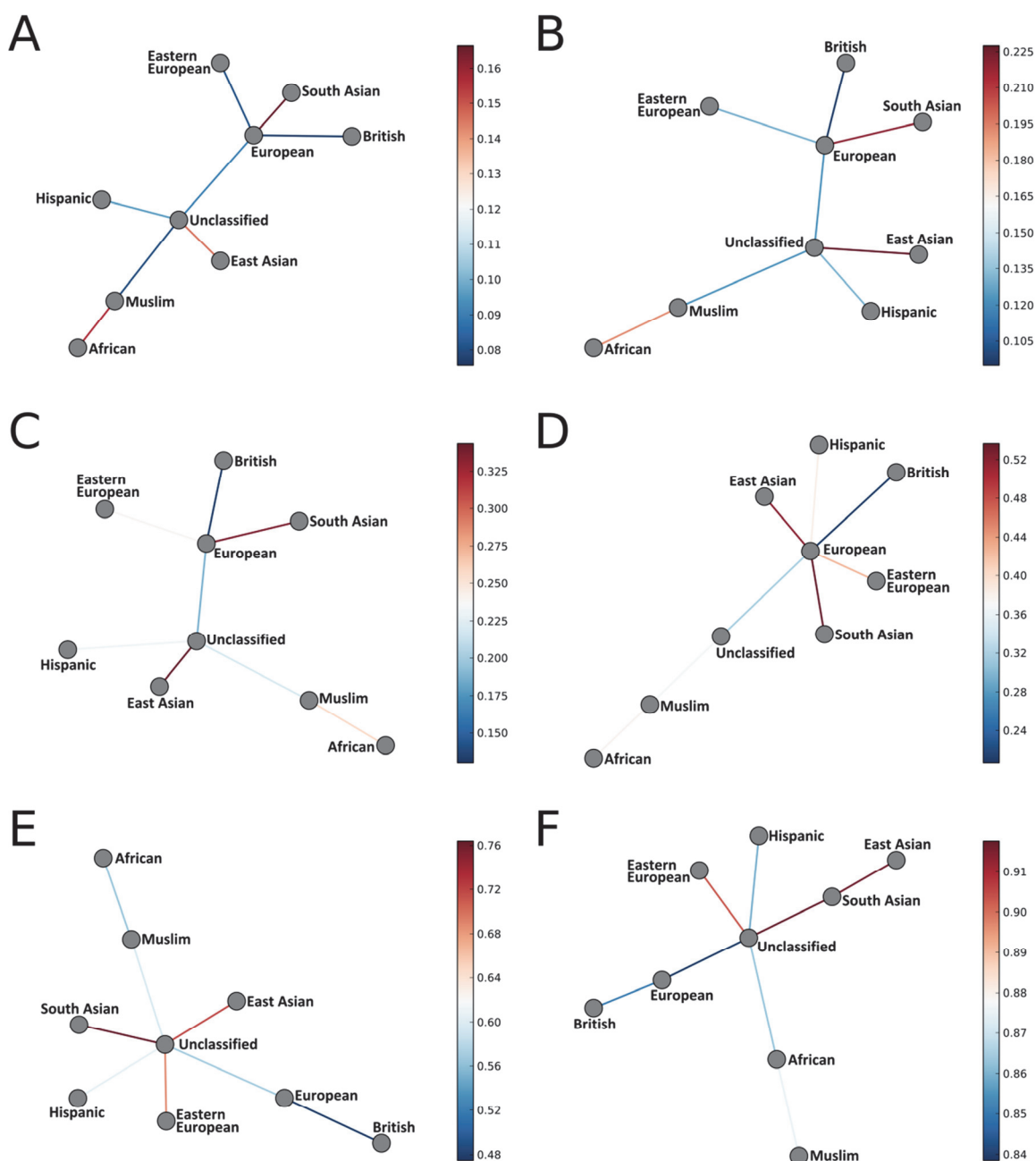


Figure 4.12: Minimum Spanning Trees for ethnic dissimilarity in Southwark at A) MSOA B) LSOA C) OA D) Postcode E) Building and F) Household levels of aggregation.

Echoing the previous charts (Figures 4.6 and 4.7), the graphs shown in Figures 4.12 and 4.13 retain stable ethnic population structures for higher levels of aggregation (MSOAs, LSOAs

and OAs), however when considering smaller spatial scales, the structure of Southwark's ethnic population changes. In both graphs the tree-like structure breaks down to some degree as the level of aggregation decreases, owing to the fact that people are more likely to live in the same household as people of similar ethnicity than they are the same street or higher level administrative unit.

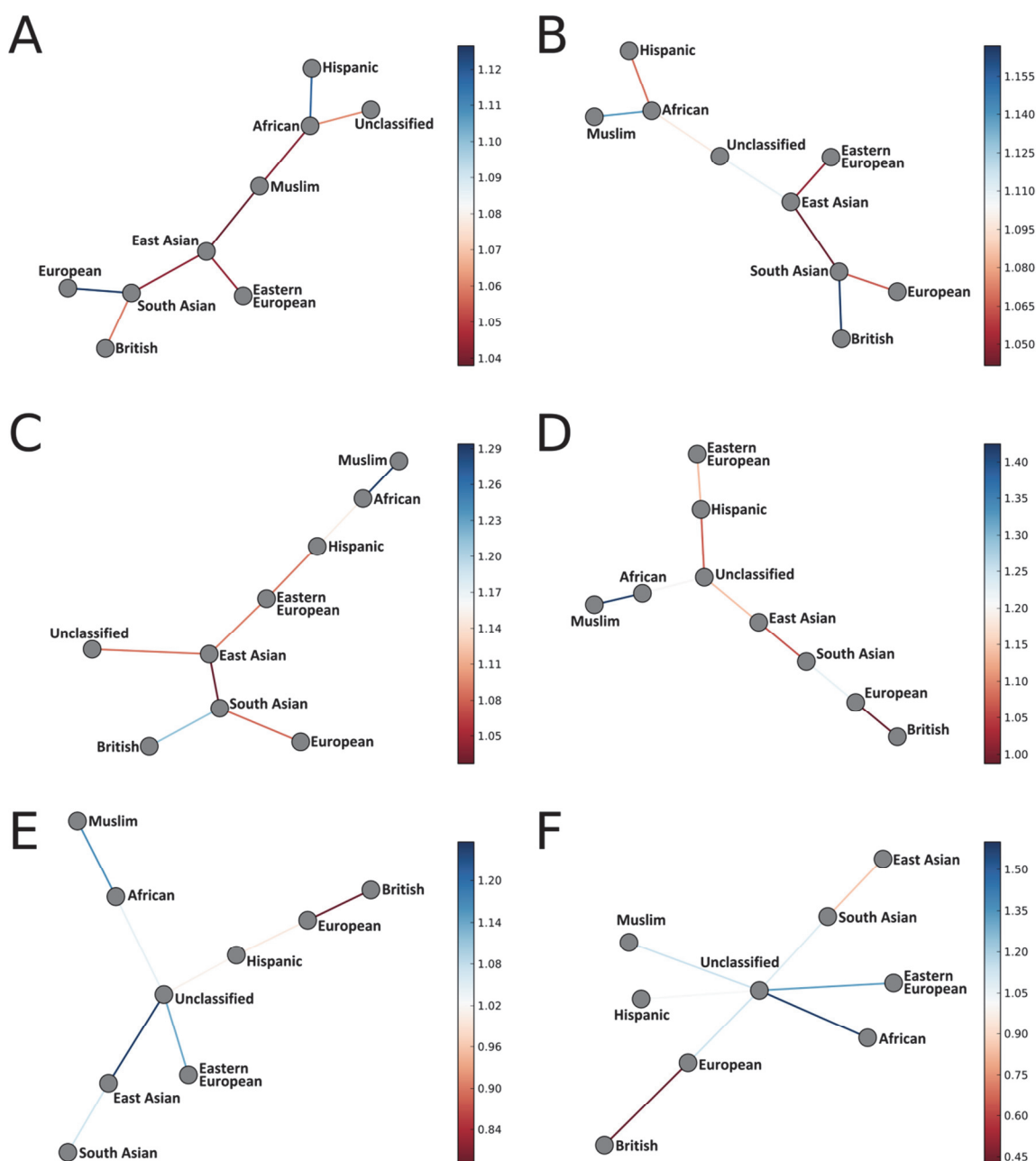


Figure 4.13: Minimum Spanning Trees for normalised ethnic interaction in Southwark at A) MSOA B) LSOA C) OA D) Postcode E) Building and F) Household levels of aggregation.

At the larger scales of aggregation, for both dissimilarity and interaction, two distinct cliques form, effectively creating a distinct grouping of European, British, Eastern European and South Asian ethnicities from particularly African and Muslim groups, but also the unclassified

and East Asian groups. This largely reflects the effect of local authority decision making with regard to social housing, as well as making light of the migration trajectories of the more recent Eastern European immigrants, and the older historical migrations of South Asian people. However, these structures break down when smaller levels of aggregation are considered, across all scales strong linkages are shown between African and Muslim groups, and British and European groups indicating that these ethnic pairs are most likely to live in similar places, and interact with each other across all scales. Interestingly, the South Asian and East Asian groups end up being more similar to each other than other ethnic groups at smaller aggregations, but are initially separate in the dissimilarity measures. Figure 4.3 shows that both East Asian and South Asian communities are somewhat multi-nucleated, thus whilst the two groups may be somewhat dissimilar at a smaller scale, at a larger scale, that of postcode, or building the two groups do actually interact with each other more than with other groups.

By the household level both dissimilarity and interaction graphs have become somewhat like star graphs, with the 'unclassified and other' group acting as the hub. This is itself an artefact of the Onomap data coding process: the classification is based on a larger dataset of British names than it is any other group, thus there is likely to be a more complete classification of names common to the British Isles and more uncertainty with regard to non-British names. As per Table 4.1, the small number of observations per household, or per building, may have an effect on the stability of the resultant indices, however the small numbers of observations per aggregation unit is somewhat countered by a greatly increasing number of aggregation units themselves. Testing for instability in the observed populations of buildings and households reveals that when the data is filtered for greater household sizes (i.e. only construct an index with at least 2, 3, 4 or 5 people per aggregation unit) the indices change, but the rank ordering of the ethnic groups remains consistent suggesting that it is appropriate for use as in Figures 4.12 and 4.13.

These depictions of ethnic group structure in Southwark using the minimum/maximum spanning tree have effectively reduced the complexity of graph depictions from the complete graph, whilst retaining connectivity in the graph as a whole. However, this approach is engineered to find the minimum weight tree, and hence will remove very low weight edges connecting two ethnic groups if each group also has an even lower weight edge connecting to another ethnic group. It is for this reason that the unclassified group

becomes so central, and also why the strong triangles of African-Hispanic-Muslim and English-European-Eastern European that seem to occur in Figures 4.10 and 4.9 respectively are not present. In order to develop alternative, and potential more structurally inclusive graphs, the next section investigates the use of multidimensional scaling as a method for opening up other ways of drawing geometric graphs to represent ethnic group structure in Southwark.

4.4.4 Multidimensional Scaling for Graphs

The effective dimensionality of a single graph, such as in Figures 4.8-10, is 9. However, it is not possible to visualise a 9-dimensional graph without making compromises; all of the visualisations of graphs shown so far are in 2-dimensions. The circular graphs in Figures 4.8-10 use classification to describe the pairwise dissimilarity or interaction between nodes in terms of the colour of the edge, however the relative location of one node to another is not significant. Similarly, in visualising the minimum spanning tree graphs in Figures 4.12 and 4.13, the aim is to separate the nodes sufficiently so that the visualisation is clear, whilst the node position is force directed based upon edge weight, again the relative positions of nodes does not necessarily represent the level of similarity or interaction between nodes.

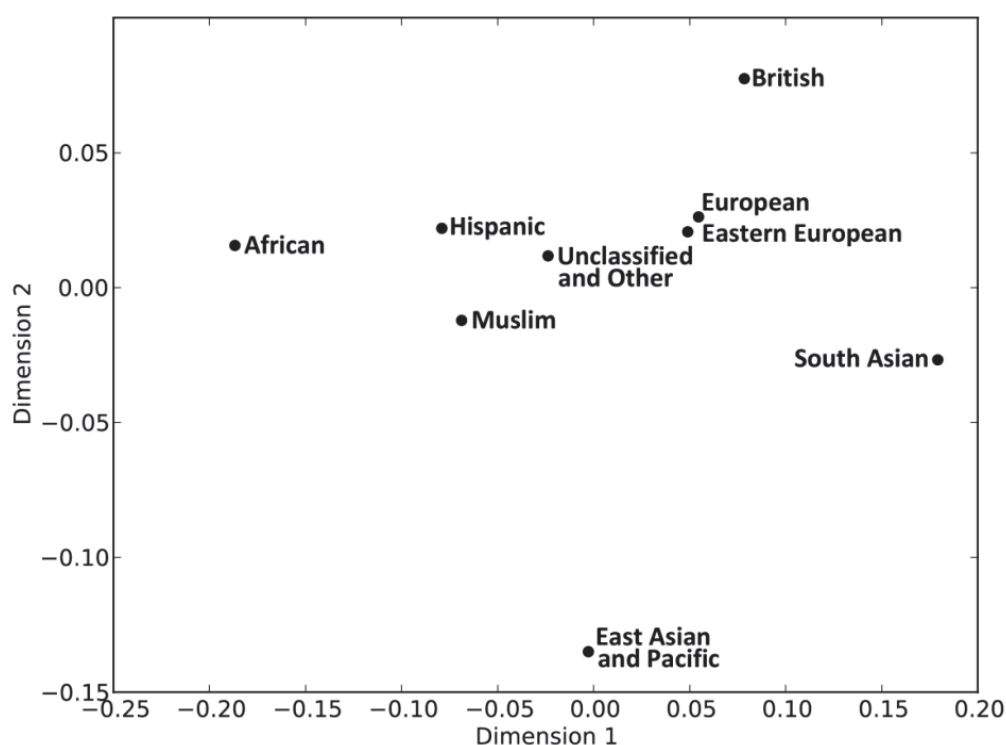


Figure 4.14: Multidimensional scaling for Southwark ethnic groups at MSOA level (stress = 0.0840)

If we were interested in placing nodes relative to their similarity or interaction with other nodes for the 9-dimensional complete ethnicity graph, we would quickly find the task to be at best inexact, and at worst impossible: this is because some strongly-connected nodes are connected to other mutual nodes with varying weights, and hence inconsistencies are introduced that cannot be directly represented in 2-dimensions.

Multidimensional Scaling (MDS) is a mathematical technique that aims to reduce the effective number of dimensions in a dataset, it works by taking a triangular matrix of pairwise distances (such as the dissimilarities or interactions in Figure 4.2) and assigns each item in the table (in this case an ethnic group) a position in N-dimensional space, where N is defined by the user prior to the process (Scott, 2000; Gatrell, 1981). The basis for MDS is that the distances in the output data match the distances in the input data as closely as possible. Using N=2 dimensions, the nodes can be mapped in a Cartesian plane, in which node proximities are indicative of the dissimilarity or interaction between different ethnic groups. The success of MDS for a given data set is measured by the "stress" incurred, that is, the reduction in "badness-of-fit" of the scaling procedure; naturally stress is reduced as N increases. Conducting MDS on Table 4.2 yields the chart in Figure 4.14.

Multidimensional scaling offers an opportunity to investigate other ways of linking nodes to form a graph beyond the MST approach already described, useful graphs might include the Gabriel network (de Smith, 2009; Gabriel and Sokal, 1969) or the relative neighbourhood graph (de Smith, 2009; Toussaint, 1980). Edges in a Gabriel network are defined by considering the context of any pair of nodes in a point pattern, if a circle can be drawn in which two candidate nodes represent the diameter, and no other nodes fall within that circle, then the two nodes are linked by an edge, otherwise they are not. This procedure is carried out for all possible pairs of nodes, and shown in Figure 4.15, an example Gabriel network for MSOA level ethnic dissimilarities is then given by Figure 4.16.

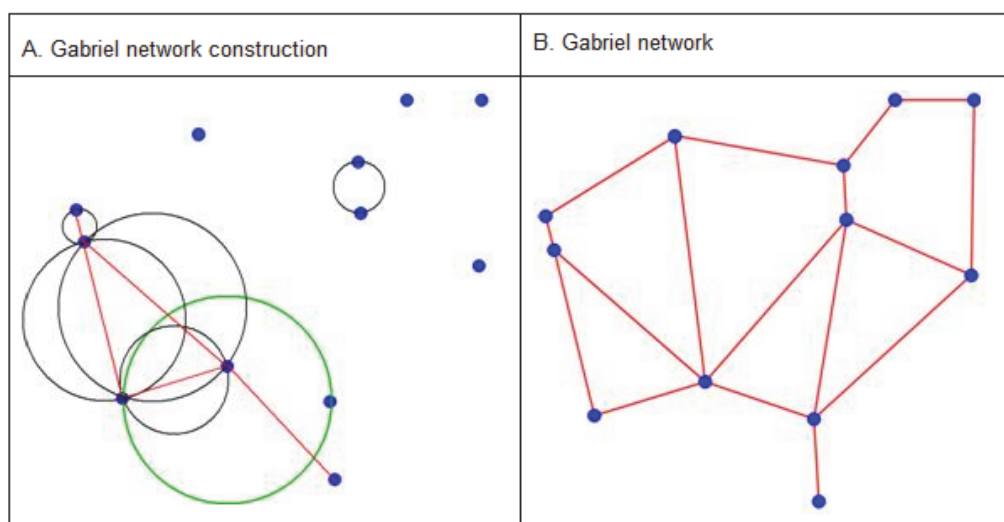


Figure 4.15: Constructing a Gabriel Network (Source: de Smith et al, 2009 p. 417 Figure 7-5)

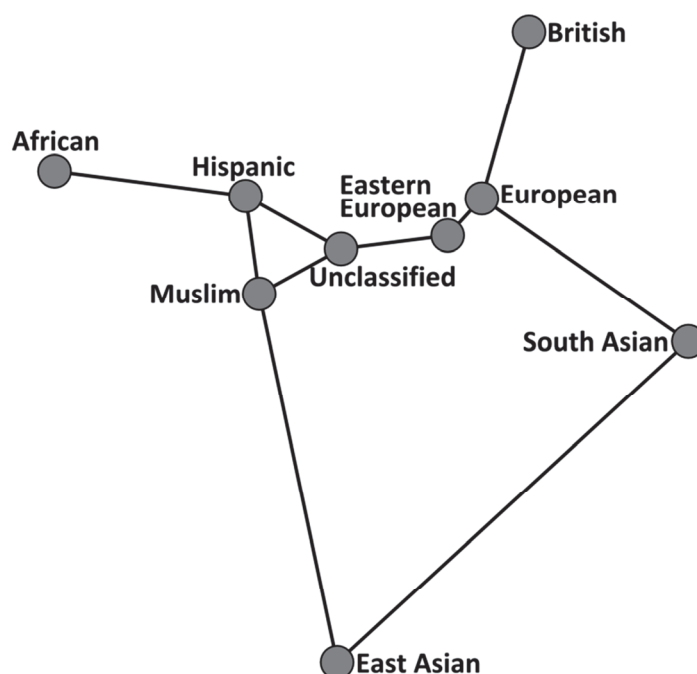


Figure 4.16: Gabriel Network based upon Figure 4.14. MSOA aggregation of dissimilarity of Southwark ethnic groups.

It is clear that the Gabriel graph adds something to the representation of ethnic group structure in Southwark, however it is difficult to draw a straightforward conclusion, if seen as a meaningful description of connectivity, the graph reveals cycles and ethnic cliques subject to segregation. However, the stress value for the MDS output, which measures fit, increases as the level of spatial aggregation decreases. When measuring ethnic group dissimilarity, only the MSOA and LSOA levels of aggregation can be considered to have acceptable stress levels (below 0.15), for the normalised interaction index multidimensional scaling is inappropriate as the measurement is not a distance-type measure (such as a dissimilarity).

What this means is that only the MSOA and LSOA index of dissimilarity values can be transformed from 9 to 2 dimensions, with relative proximities in 2-dimensions ably representing the 9-dimensional dissimilarities; smaller aggregations produce an output from MDS, but the proximity of nodes are likely to be misleading. Thus the usefulness of this approach is diminished compared to those already discussed, although it may be of interest at higher scale aggregations.

4.5 Consolidation

This chapter has demonstrated several interesting aspects relevant to developing a contextual understanding of a population through spatial health information. At the most primitive level it describes the general character of Southwark as articulated through ethnic, cultural or linguistic groupings derived from the Onomap classification. Indeed, some of these descriptions are quite sophisticated in their own right, and provide both a spatial and structural insight into residential segregation. Highlighted along with the quantitative insights gained is the need for mixed-methods approaches, any conclusions drawn from the analysis and visualisation shown without the insights that come from Carter's (2008) work on residential segregation in Southwark could easily be misleading.

What is not misleading, however, is the effect that different aggregations, and the Modifiable Areal Unit Problem, have on the indices investigated. Particularly interesting are the changes that occur to the ordering and connectivity of different ethnic groups at small areal levels of aggregation. It has long been known that "relationships typically grow stronger when based on larger geographic units" (Longley et al, 2011 p. 171), and Wong (1997) demonstrates this is true in segregation studies. Wong (1997) states that "large areal units usually result in low segregation measures" (p. 128), which is certainly true in Southwark, and that there is usually positive spatial autocorrelation to be found between members of the same ethnic group, which can explain why smaller areas tend to have higher segregation measures – if ethnic groups are likely to be clustered, and a small area is considered, then there is less opportunity for there to be multiple ethnic groups within a small area than a larger one. Therefore, the fact that groups become more segregated as the size of areal aggregation decreases reveals more about the scale sensitivity of the indices than it does about segregation per se. However, changes in the rank, and rate of increase, of the segregation measure of an ethnic group relative to the other ethnic groups can reveal interesting trends

in the spatial behaviour of that group. If for instance a group has a similar level of segregation as other groups at a regional level, but has a comparatively higher rate of segregation at sub-regional aggregations then this is an indication that the group in question is subject to significant positive spatial autocorrelation. Conversely, groups that display a comparatively slower rate of increase in the value of their segregation measure are likely to be more dispersed across the region at sub-regional scales.

In Southwark, relative stasis and similarity seems to exist in the measurement of dissimilarity and interaction of ethnic groups at the areal aggregation of government disseminated statistics (MSOAs, LSOAs, OAs). However, the rate of increase in the value of the dissimilarity and interaction-based segregation measures, and the ordering of ethnic groups, varies between groups at postcode, building and household levels of spatial aggregation; these structural changes point to the existence of particularly local segregation effects which are otherwise unaccounted for at more generalised scales. This is likely a result of historical factors in addition to the urban ecology of Southwark, indicating that there may be significant local variations in segregation indices to be found in other densely populated urban areas, particularly those with high population churn, a large minority population, large stocks of social housing and local processes of isolation and gentrification in effect. It is important to note that the small areal units which display the most volatility in the ordering of ethnic residential segregation are not usually considered due to the difficulty of obtaining data at that level.

The chapter also demonstrated a set of graph-based method for representing and visualising complete and tree-like graphs of pairwise segregation measures. It is argued that these are effective in representing the similarities or interactions between groups graphically, although the issue of the multidimensionality of the data is a confounder. The complete graph is an effective visualisation, however it is complex, in which case the minimum spanning tree approach allows a simplified look at data across many scales. The data is visualised for areas traditionally related to the aggregation and dissemination of demographic statistics, however there is no reason why another aggregation scheme cannot be used, these final two graphs (Figure 4.17 A & B) demonstrate the complete graph structure for ethnic groups if the GP surgery is used as an aggregation.

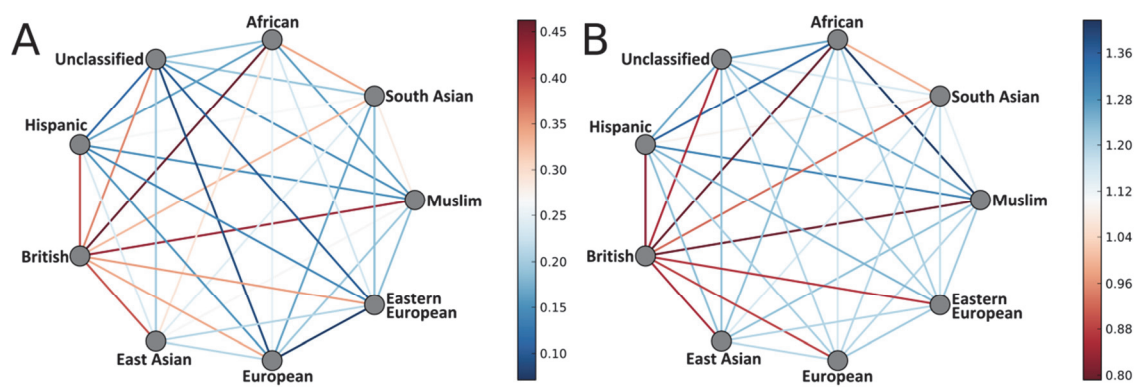


Figure 4.17: Segregation indices for Southwark GP surgeries A) index of dissimilarity and B) normalised interaction index

The patterns suggested in Figure 4.17 are indicative of the kind of behaviours associated with patient registration that are investigated and analysed over the course of the next three chapters.

5 General Practice Surgery Patient Register Composition in Southwark

5.1 Introduction

This chapter explores patient registration with Southwark GP surgeries, characterising access to surgeries in terms of the distance, and travel time, from the patient's registered address at their GP surgery of choice. This builds on the exploratory analysis of "potential" to access a GP surgery discussed in Chapter 3, and also introduces a location-allocation focussed strand of health services research. The overarching intent of this chapter is to create a normative model of service delivery for Southwark GP surgeries, by minimising the accessibility constraints (travel distance/travel time) for all patients. The resultant model, it is suggested, can then be used as a counterfactual; by controlling for the effect of distance in this way, other socio-demographic characteristics which define a particular GP surgery's composition can be foregrounded in order to better understand the basis for patient choice.

The chapter begins by considering how normative models and theory fit into an understanding of healthcare provision, drawing on "central place theory". Subsequently, the measurement of distance and time travel within a GIS is highlighted for the Southwark area, and variations in these data with respect to patient registration behaviours are demonstrated. Voronoi polygons are computed from the spatial distribution of patients as a basis for zoning, and a distance matrix based upon this zoning is created in order to pose a linear programming problem known as "the transportation problem". Solving the transportation problem gives rise to the set of non-overlapping zones that describe the optimal arrangement of patients in order to minimise the distance to GP surgeries. The discrete neighbourhood zone defined for each GP surgery may also be a better representation of Southwark's geography of primary care than is otherwise available through pre-existing administrative districting. This in mind, the resultant set of zones is also a yardstick for the rationality of the distribution of GP surgeries, Mayhew (1986) notes that:

"[P]atients, the consumers of health care, are partly guided by their own judgement about whether to use particular facilities. Such judgements are determined by many factors, one of the most important of which is accessibility" (p. 8)

Determining the varying importance of accessibility and other factors requires a sound knowledge of the structure of a spatial system, which is investigated through the use of exploratory spatial data analysis (ESDA).

5.2 Normative Models of Spatial Structure

5.2.1 Isotropic Planes: an Introduction

The legacy of urban public facility location provides a useful contextualisation of the importance of normative locational theories, and indeed one relevant to the provision of healthcare within a welfare state. DeVerteuil (2000) suggests that the late 1960s marked the beginning of a practical exploration that integrated normative and spatial concepts, emerging with a definition of spatial optimality that sought to balance the efficiency and equity constraints of locating urban public facilities. Such an approach is based upon modelling reality, using symbolic models (cf. Longley and Batty, 2003) which employ mathematical and statistical relationships to shed light on otherwise complex circumstances. Taking a normative approach suggests that a problem ought to be expressible in terms of an objective function, which is a mathematical representation of the key criteria that determine the solution to the problem at hand. The objective function will give rise to a number of possible solutions, from which the best available solution that can be found is taken to represent the optimum solution- the normative model of “what ought to be”.

The application of normative models necessitated a systematised way of thinking about the world, which Chisholm (1967) introduces in the following way:

“all things (as objects primarily but also as ideas) have connections with many other things and the significance of any one depends on its relationship with others. Hence, the unit of study should not be a single thing but a system of interrelated objects or ideas.” (p. 45)

David Harvey (1973) is rather more forthright when he describes the need for “the city to be regarded as a functioning totality” (p.303). Harvey uses these words in particular to convey the enormity and difficulty of seeing the city in this way, and the inevitable requirement for partial analyses.

Within health and medical geography, Thomas (1992) employs a systems way of thinking in order to impose a common analytical form on a subject area that crosses numerous

disciplinary boundaries, he describe the result with the term “geomedical systems”.

Interrogating a system will reveal the values of the continuous attributes, or discrete states, which comprise the nature of the system, and describe its behaviour at a given point in time. Whilst Thomas (1992) defines several distinct geopolitical systems as they relate to disease diffusion, the system that is most pertinent to this thesis governs the provision of healthcare to the public. Thomas (1992) discusses the normative objective of creating a “static equilibrium” that support a rational set of relationships balancing demand for, and supply of, healthcare services, which serves a neoclassical goal. The system is defined by the requirement to satisfy a range of planning objectives, which defines the objective function in the normative model: minimising patient travel time to GP surgeries, for instance. Control is thus fundamental to normative models, and Tan and Bennett (1984) note that it:

“concerns the choice of disposition of a set of instruments or policy variables affecting different spatial locations to achieve a given objective function which is spatially variable so as to satisfy a set of system properties” (p.1)

Of course, control relates to those variables that can actually be manipulated in order to induce the system to better approximate a desired output state. In many cases we have to accept that some variables are fixed, in the case of allocating patients to GPs the pre-existing location of GP surgeries, for example, is immutable. This is because changes in the system take time and require careful planning, they do not simply evolve or emerge, and for this reason Thomas’s (1992) conceptualisation of the healthcare system allows it to be essentially static.

Spatial systems, such as the local system of GP surgeries that delivers primary care in Southwark, are conceptualised in a common way – as a set of zones which interact subject to the properties governing the behaviour of phenomena within each zone (Tan and Bennett, 1984). Thomas (1992) notes that the most long-standing approach to assigning patients to care takes its cues from Central Place Theory.

5.2.2 Central Place Theory

Christaller (1933) articulated Central Place Theory based upon observations of the location and structure of towns and cities in southern Germany (Figure 5.1). It was meant as an explanation of the existence, and distribution, of different retail services, providing goods of varying attractiveness, within the urban hierarchy in accordance with the threshold of

population required to support the existence of a service. Wilson (2000) details the assumptions that Christaller introduces in his analysis: that people are assumed to minimise travel distance to services; retail services are assumed to maximise profits; there is a uniform underlying population, which has a uniform purchasing power; there is an isotropic plane – abstract space characterised by a homogenous, featureless surface, upon which central places develop.

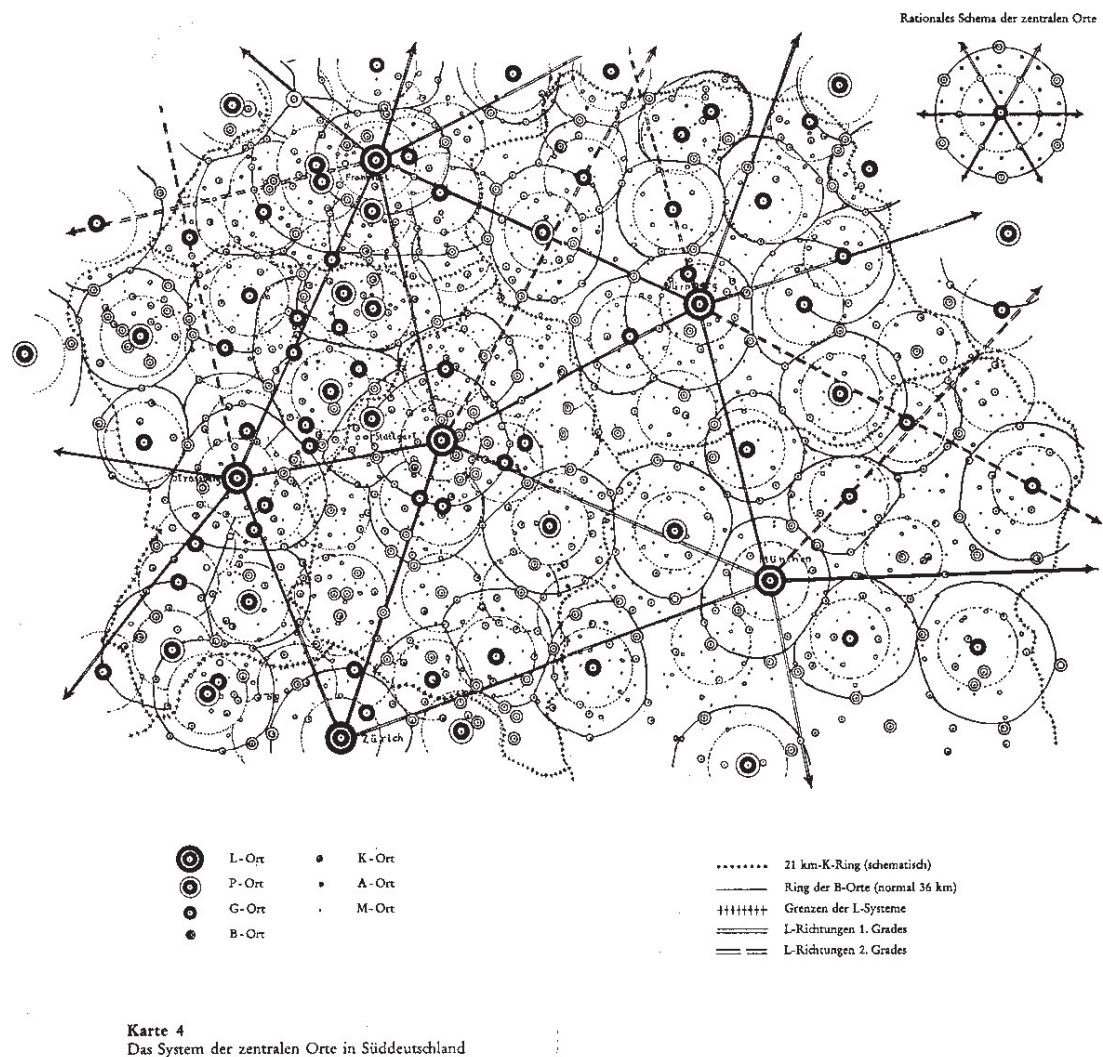


Figure 5.1: “Das System der zentralen Orte” – The system of central places (source: Christaller, 1933)

Christaller uses two important concepts in formulating Central Place Theory, range and threshold: the range of a good dictates the maximum distance that consumers would be willing to travel in order to purchase the good; and threshold is the minimum area, or population size that is required to support a good, i.e. to make its sale profitable. Using these concepts, and the aforementioned assumptions, Christaller is able to suggest the geometry of a system of central places – if all places are to be served without overlap then,

as shown by Haggett et al (1977), there exist only 3 possible types of regular polygon to achieve this which keep area constant: equilateral triangles, squares, and hexagons, wherein hexagons are most efficient at “space-packing”. For a set of centres of the same order, i.e. equally sized cities, a single hierarchy of hexagons will exist, however, for a variety of different orders of centre, or for goods that have a lower range than is accommodated by the size of the market area implied by the hexagonal tessellation, larger and smaller tessellations of hexagons can be created that overlay each other. This creates a hierarchical set of central places dependant on the goods sold at a given location, and allows for a complete coverage to be made based upon varying orders of goods: such a situation is exemplified in Figure 6.1 with the existence of different sizes of “Ort” (place) denoted by letters (e.g. G, B, K A etc.).

Mayhew (1986) suggests that the general principles underlying Central Place Theory are useful to public healthcare provision in urban settings due to the focus on accessibility, and the fact that consumption of a retail good can be seen as a demand, or need, on behalf of a population for healthcare services. Thomas (1992) speculates upon a theoretical system of central places for the UK NHS in which GP surgeries make up the lowest hierarchical tier, providing general medical services to a local population, whilst outpatient and inpatient care comprise an unspecified number of additional hierarchies dependant on hospital specialisation. In this sense, the central place framework is a normative theory that seeks to optimise delivery in some form. Although it makes too many assumption to be of practical value, it does, however, inform the trajectory of public facility location through the advent of location-allocation techniques.

5.2.3 Spatial Models in Healthcare

In Chapter 3 a number of approaches to modelling potential were introduced with respect to accessing GP surgeries. These models are driven by an analytical desire to assess “what is” with respect to health care circumstances; Knox (1978) for instance uses accessibility as a basis for exploring “social or community wellbeing” in Scotland, concluding that its “intraurban ecology” is such as to suggest that worse off areas in the cities studied are under-served by doctors. There are numerous modelling approaches of this type, with several basic approaches detailed by Ricketts et al (1994). As has been suggested, normative models are about more than “what is”, instead capturing some measure of “what ought to be”. These models are often referred to as “location-allocation” type models, and focus on

efficiency and optimisation primarily rather than purely the distributional justice of a healthcare system. Cromley and McLafferty (2002) make the important point that in such models, the ideals and optimums are usually defined by decision makers external to the community setting that will actually be affected. This leads to an important consideration, and one that has received considerable focus with little resolution, is it possible to reconcile efficiency and equity considerations? Symons (1971) ponders:

“One may ask whether a point in space has attributes of equity as well as efficiency, i.e. whether a spatial relationship can be determined which relates the legal requirement for equity with the resource constraints which require efficiency” (p. 54)

Chapter 1 considered “equity” in its various forms. However, it is important to pick up the meaning of efficiency in a spatial context, which Symons views in terms of optimal location: “a set of locations is said to be efficient if no further spatial adjustments to the set could be made which would make anyone better off without making anyone else worse off” (1971, p. 55). This is actually a particular form of optimality common to welfare-based approaches (cf. Smith, 1977) known as “Pareto Optimality”, Harvey (1973) explores this idea to some depth, basing his inquiry on the notion that:

“policy proposals for the more effective organization of space cannot take it for granted that a mutual benefit to all will result” (p. 238)

This is echoed by Smith (1977) who wonders how to ensure that “benefits and penalties” are “apportioned among the population in a predictable and equitable manner” (p.23). Harvey goes as far to suggest that “optimising the city is a meaningless phrase”, as the structures in place will always favour those people with the means to succeed. Harvey cites John Rawls, whose “theory of justice” (1972) gives rise to the Maximin principle that social and economic inequalities ought to be arranged to maximise the minimum level of benefit available to the least well-off in society. To this end, normative models have proven effective, but are not without practical considerations – Messina et al (2006) use allocative models to assess optimal access to existing hospitals, and compare the results with a normative set of hospitals in order to identify underserved areas; likewise Densham and Rushton (1996) find that some services whose existence has a political dimension require the normative solution to be adjusted in order to ensure the viability of rural facilities perceived as important.

5.2.4 Consolidation

There is a natural contrast in analysis between models that provide an assessment of a given distribution observed in reality, and models which seek to specify what ought to be, under certain conditions. Just as Harvey (1973) is sceptical of the ability of normative models of systems to treat anything beyond partial representations of the system fully, Thomas (1992) too notes that “the planning of health service delivery is something of a compromise” (p. 28). Indeed, a purely theoretical approach to healthcare systems will result in the drawing of absurd conclusions – clearly healthcare cannot exist under the paradigm of central places, and yet it provides a compelling starting point to thinking about how social behaviours actually affect the extant fairness of a system. This is what Smith and Harvey are wrestling with in their work on social justice; the apparent objectivity of optimisation approaches can lead us to believe that a simple, clean solution can exist to problems of distributive justice, and on the surface this may be true. However, at the heart of social justice are a set of power relationships that warp the relationships between the social, political and economic experience of place, creating a subjective reality that varies from individual to individual and is subject to their position in society. Thus as Harvey suggests, optimising the city seems to be a strange and difficult topic to reconcile with the extant complexity of social systems.

This chapter investigates the extent to which Central Place Theory can legitimately play a role in understanding the patterning of registrations with GP surgeries. This is done by creating a set of non-overlapping “market areas” for each GP surgery subject to the capacity of each surgery. These market areas are based solely upon minimising the distance or travel time of patient to access a GP surgery, and hence can be thought of as a “counterfactual” – a model that imagines an alternative reality in which patients value only the condition that a GP surgery is as close as possible to their home. This allows us to explore how registration with GP surgeries differs between the counterfactual and the observed reality. In this way deviations from a simple normative understanding will highlight the extension of spatial inefficiencies across a system of local provision, and may provide demographic insights into patient registration behaviours, be they preference or constraint based. To provide context to this study, the next section investigates observed patterns of registration to GP surgeries in Southwark.

5.3 An Exploratory Spatial Data Analysis of Patient Registrations with GP Surgeries in Southwark

Exploratory spatial data analysis (ESDA) concerns the description and exploration of spatial datasets (de Smith et al, 2009). This includes spatial and non-spatial visualisation, the computation of descriptive statistics and the examination of data distributions. Firstly, the methods for calculating distance and travel time are elucidated, and subsequently an analysis of registration data for patients of Southwark GP surgeries is undertaken.

5.3.1 Network Distance and Travel Time in Accessing GP Surgeries

GP surgeries provide a location-based service; most of the time in order to access care a patient will have to travel to the GP surgery with which they are registered. Firstly, we make the assumption that in order to access their GP surgery, a patient will travel from their recorded address to the address of their registered GP surgery. Secondly, we assume that calculating the shortest route (either by distance, or travel time) between a patient's household and their GP surgery is a useful representation of their travel behaviour. Finally, we assume that in the case of defining a distance that patients are constrained to the street network as described by the OS Mastermap Integrated Transport Network (ITN) Layer, and in the case of public transport travel times they are constrained to walking and using the bus network.

Network distances are computed in ArcGIS 10 Network Analyst using the OS Mastermap ITN layer. The network distance is intended to represent a walking distance, because distance to GP surgeries in Southwark is low and car ownership in Inner London is also low, we thus assume that there are no turn, or direction, restrictions on the network. Aside from walking, it is also likely that patients will choose to use public transport to reach their GP surgeries, thus a travel time is modelled based upon patients using the bus network if it is quicker than walking. The bus stops and timetable information is available from Transport for London (TfL) and a peak-time travel measure is computed. Train and tube modes were not used because of: the local nature of registration with GP surgeries; the complexity of modelling these additional modes; the increased computation time required; and the fact that Southwark's public transport infrastructure very much hinges on the use of buses: there is a very limited tube network, and the train network covers large distances between stops. We

assume that all patients are in a position to pay for a bus ticket if it proves faster for them to access their GP surgery than if they were to walk.

Travel times are computed using a system designed for the UCL Centre for Advanced Spatial Analysis's (CASA) Arcadia project (EPSRC, 2010). The system computes travel times for the London region between small areas based on the multi-modal use of the transport network. CASA uses this as an input into a land use transport model (LUTM) for the London functional region, however, the high precision of the transport infrastructure represented in the system means that it can compute travel times effectively at the household scale. The system computes the shortest journey between two points, using the bus network if it is faster than walking, making the following assumptions on travel: walking speed is 3.5 mph; the time spent waiting for, or changing buses, is half the timetabled time between buses arriving at a stop; bus travel time between stops is governed by TfL reported travel times between stops, and is extracted for peak-time (9am) in order to test the sensitivity of the travel time analysis against network distance. Computing travel-time between all households in Southwark, and all the surgeries that Southwark patients register with is computationally intensive, taking five days to complete.

The two most important values computed are the distance, or travel time, to the nearest GP surgery, and to the GP surgery actually used. The rank of the GP surgery used is also computed, based upon the number of GP surgeries that are closer to the patient than their GP surgery of registration. In cases in which there is more than one GP surgery in a single building, they are treated as having a tied rank. There are three GP surgeries which have multiple surgery locations: two GP surgeries with two locations; and one GP surgery with three locations. Unfortunately the Southwark patient register provides no indication as to which branch a patient is specifically registered with, so in this case the distance computed to these surgeries for each patient is the distance to the nearest branch.

5.3.2 System Characterisation

In exploring the characteristics of the system of local provision by GP surgeries in Southwark, a simple axiom is used, that a hypothetical "normative accessibility" can be represented by a patient's distance, or travel time, to their nearest GP surgery, whilst their observed registration with a GP surgery represents their "revealed accessibility" (Higgs, 2004; Joseph and Phillips, 1984). Patterns of revealed accessibility may give us an insight into the

behaviour of patients in Southwark: furthermore, it may give some clues as to whether health needs are being met. However, it is important to note that the pattern of revealed accessibility is subject to endogeneity, it is likely to be the result of both: explicit patient preferences as to the GP surgery used, and the effect of systemic constraints on access to healthcare.

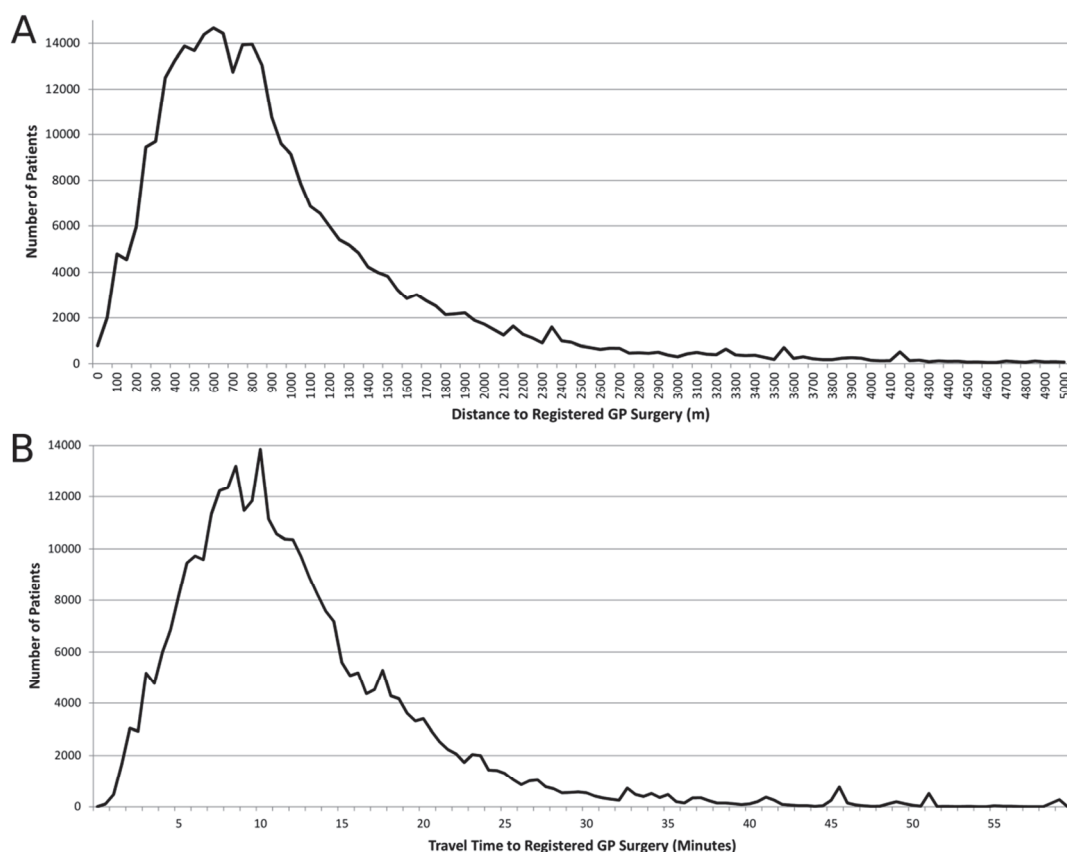


Figure 5.2: Distance (A) and peak travel time (B) distributions for patient registrations with Southwark GP surgeries.

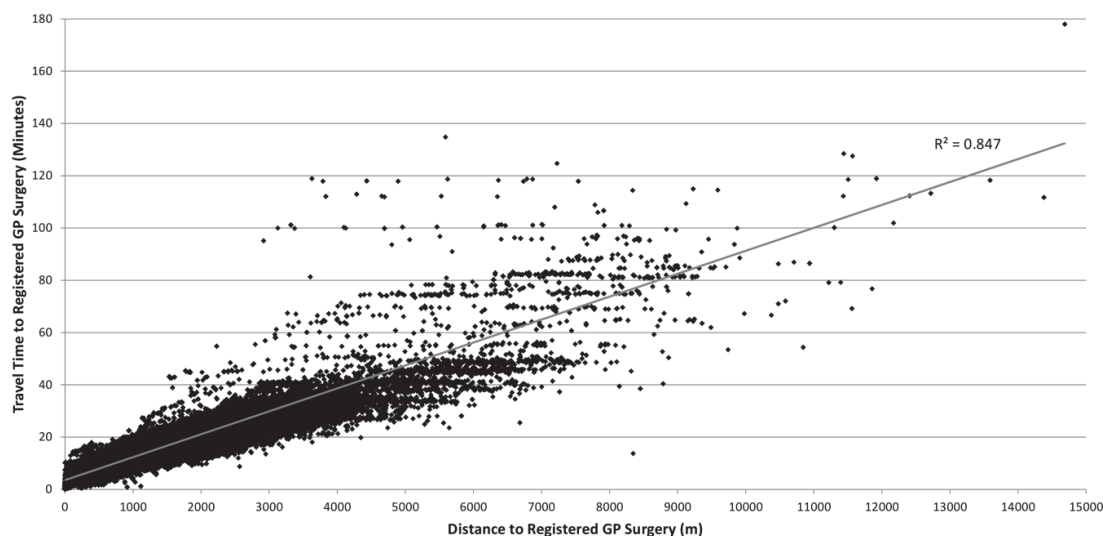


Figure 5.3: Relationship between patient distance and travel time to GP surgery

Figure 5.2 is a histogram of distance (5.2A) and travel time (5.2B) by the frequency of patient registration with a GP surgery. Figure 5.3 demonstrates that there is a strong linear relationship between bus travel time and network distance to GP surgeries; a fitted line gives an R^2 goodness of fit of 0.847. Comparing the identification of whether a patient uses their nearest GP surgery or not reveals an 88.4% agreement in the outcome between distance-based and travel time-based metrics.

Comparing the distribution of all patients in Southwark using their registered GP surgery, as opposed to their nearest GP surgery, gives rise to Figure 5.4, which shows that there are differences between the normative and revealed accessibility of patients. It also emphasises the density of provision of service, if all patients were able to use their nearest GP, everyone could be served within 1.5km, or 20 minutes, however, the observed pattern deviates from this introducing geographic inefficiencies into the normative distribution.

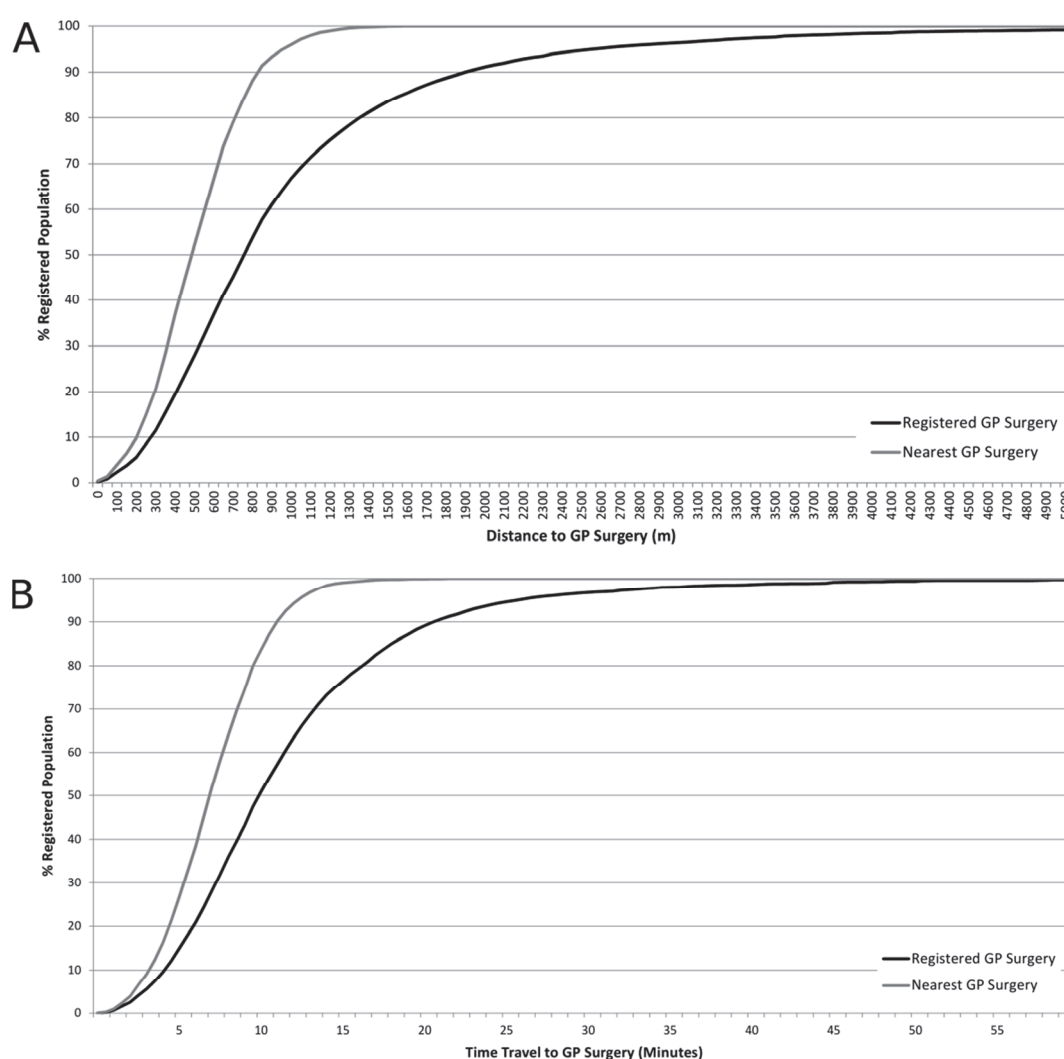


Figure 5.4: Cumulative frequency of (A) network distance and travel time (B) to nearest and registration GP Surgery

If each patient is then assigned a rank based upon the distance, or travel time, to the GP surgery they register with, where a rank of 1 suggests that they use their nearest GP surgery, rank 2: the second nearest, and so on, then the distribution of ranks of GP surgery used can be shown (Fig. 5.5). Figure 5.5 demonstrates the relationship for distance, but an equivalent relationship is found for travel time as well. Like Figure 5.4 this demonstrates the long-tailed effect of GP registration, in which c. 40% of Southwark residents use their nearest GP surgery, and 80% of residents use one of their nearest 6 GP surgeries, but 10% of patients of Southwark GP surgeries are registered with a surgery that is greater than rank 12. This suggests that a large number of patients are either willing to, or required to, make small trade-offs in accessibility against other considerations in registering with a particular GP surgery, whilst a small number of patients make quite significant distance-based trade-offs.

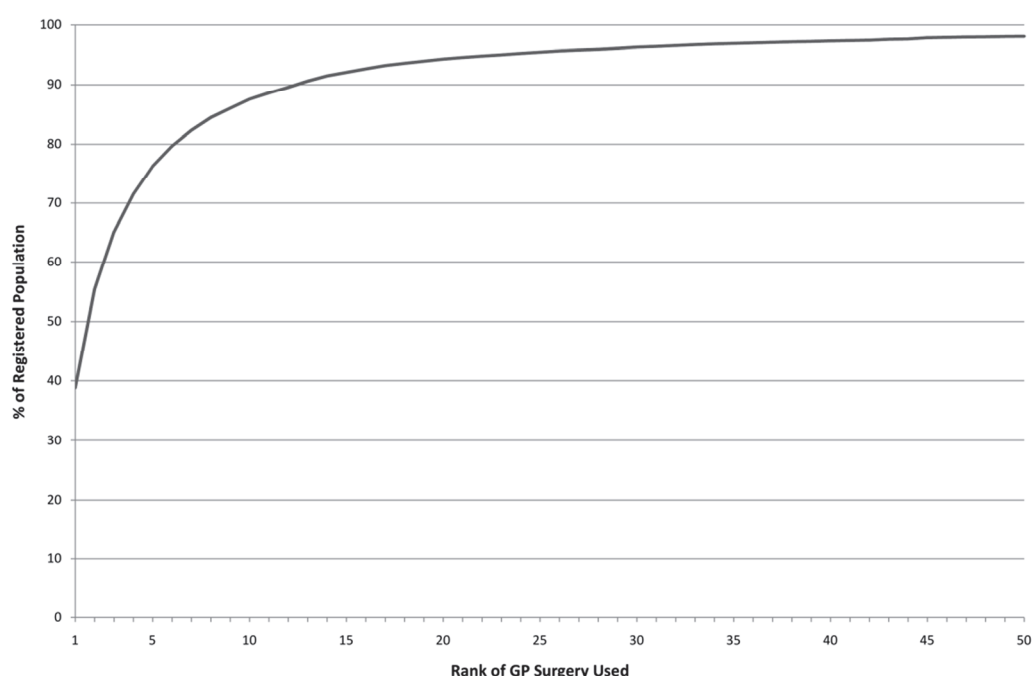


Figure 5.5: Cumulative percentage of GP surgery registration by rank

Taking the normative accessibility of a patient to their nearest GP surgery from each patient's revealed accessibility gives the additional distance, or travel time, they forfeit in order to visit their GP surgery of registration, Table 5.1 shows the magnitude of these additional distances and times by rank of GP surgery used.

An average additional 790m (7.64 minutes peak travel time) is travelled by almost 200,000 patients to use a GP surgery other than their nearest, with the median additional distance approximately 479m (5 minutes peak travel time). This preponderance of short additional distances again provides good evidence for patients exercising choice in some form.

Rank Order	Percentage of Patients (Cum.)		Sum additional travel		Mean additional travel		Median additional travel	
	Net. Dist.	Travel time	Dist. (km)	Travel time (hrs.)	Dist. (m)	Travel time (min.)	Dist. (m)	Travel time (min.)
1	39.4	36.5	0	0	0	0	0	0
2	55.8	55.5	11,226	2130	210	2.33	151	1.72
3	65.9	67.2	11,546	2440	352	3.84	293	3.22
4	72.2	74.3	10,269	1970	500	5.12	440	4.58
5	77.0	78.9	8,721	1568	566	6.21	550	5.88
6	80.4	82.1	7,659	1395	684	8.06	641	7.81
7	83.1	84.6	6,544	1193	766	8.96	749	8.58
8	85.0	86.4	5,463	945	844	9.35	799	9.42
9	86.8	88.1	6,790	1032	1,211	11.72	975	10.62
10	88.2	89.3	4,787	757	1,066	11.40	953	11.65
11	89.1	90.4	3,454	697	1,096	11.95	1,004	11.62
12	90.1	91.2	3,897	575	1,247	12.84	1,119	12.77
≥ 13	100	100	75,389	10719	2,337	22.40	1,865	18.20

Table 5.1: Additional distance travelled to GP surgery by rank

However, there is a geography to distance travelled in Southwark: the distribution of patients travelling additional distances is not random, as demonstrated by Figure 5.6 which uses a smoothing approach to spatially represent the percentage of patients at a given point in space using their nearest GP surgery. This approach is similar to the relevance and commitment methods of investigating medical service areas in Ricketts et al (1994), however it goes beyond the use of pre-existing areal units. The pattern suggests that there is a variable distance decay effect in the percentage of patients registering with their nearest GP surgery, with “islands” of higher registration forming close to GP surgeries. Arguably, this map of interaction hints at the presence of particular market areas for GP surgeries as hypothesised by Central Place Theory. The hierarchical ordering principle inherent in Central Place Theory would hence imply that some GP surgeries offer higher order services than others, which may explain the dominance of some centres in Figure 5.6, and the relative insignificance of others. Patients may be more likely to use their nearest GP surgery, even if they were a greater distance from it and had alternative choices that were as close, if that GP surgery offered additional value. Larger GP surgeries, often styled as community health centres have the resources possible to offer minor outpatient procedures locally, increasing the efficiency with which patients can be seen, they may also offer better opportunities to access care by employing more GPs. Chapter 7 reinforces this conjecture, suggesting the patients are more likely to use their nearest GP surgery if it is larger (in which the number of full time GPs is used as a proxy for size). However, the strength of the patterning of use of

nearest GP surgeries in Southwark demonstrated in Figure 5.6 may also be being confounded at the individual level by the effect of patients moving house without changing their GP registration.

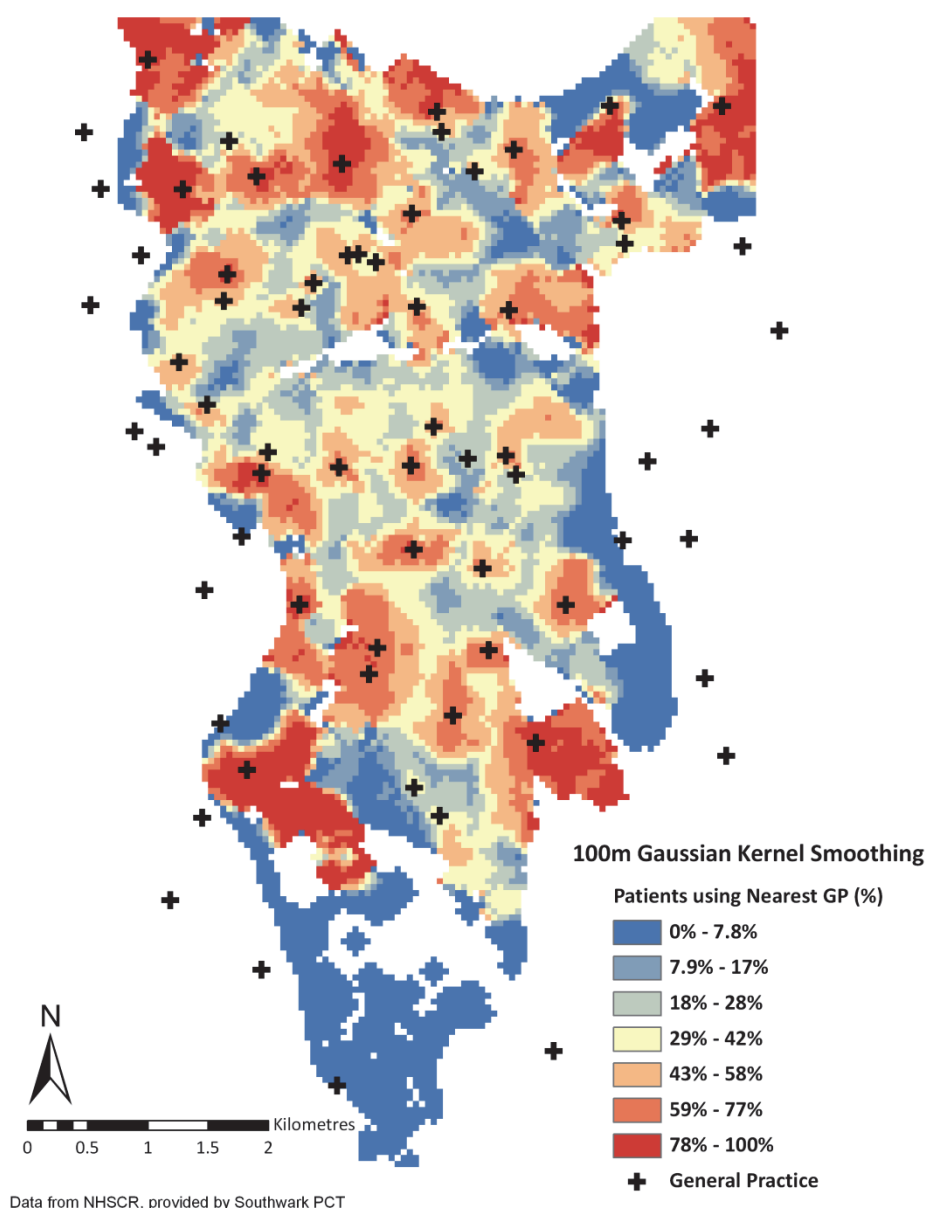


Figure 5.6: Percentage of patients using their nearest GP surgery. Gaussian 100m kernel smoothing

A similar take on patient-GP surgery interaction can also be made by looking at the direction and variability of flows from patient residences to their GP surgery of registration using Brunsdon and Charlton's (2006) local method for interpreting directional data. This allows us a simple insight into the issue of confounding individuals who live close to a GP surgery, but do not use it. The angular direction from each patient to their chosen GP surgery is calculated based upon the angle of the straight line drawn between the patient

and the surgery; a mean can be calculated by first representing each angle as a complex number of the form:

$$z = \cos \theta + i \sin \theta \quad (5.1)$$

Thus, the weighted mean direction (equation 5.2), and weighted circular variance (equation 5.3) are shown below in which w_i is a spatial weight derived using a Gaussian decay function specified by Brunsdon and Charlton (2006) in equation 5.4, where d is the distance between the point for which the mean direction is being calculated, and the observation, and b is the bandwidth of the Gaussian function representing the distance decay.

$$M_z = \frac{\sum_{i=1}^n w_i z_i}{|\sum_{i=1}^n w_i z_i|} \quad (5.2)$$

$$v = 1 - \frac{\sum_{i=1}^n w_i z_i}{|\sum_{i=1}^n w_i|} \quad (5.3)$$

$$w_i = \exp(-d_i^2 / 2b^2) \quad (5.4)$$

Figure 5.7 shows the mean direction (5.7A) and the mean circular variance (5.7B) for patients registering with Southwark GP surgeries. The variance measure is normalised between 0 and 1. Like Figure 5.4 it demonstrates the complexities of registration, showing distinct patterns in the patient flows to GP surgeries in some areas, and in others the patients in similar areas are shown as registering with GP surgeries in different directions. Both Figures 5.7A and 5.7B are shown as registering with GP surgeries in different directions. Both Figures 5.7A and 5.7B suggest that areas with a greater opportunity to access one of many GP surgeries, i.e. areas that are comparatively service-dense, are more likely to have patients using one of multiple nearby GP surgeries but not necessarily the nearest. This is demonstrated by the increase in variance of the circular mean, which implies that there is less consistent a direction of travel being taken. Where the opportunity to choose between several GP surgeries is less, the variance is notably lower, as most patients choose to travel to the same GP surgery. In some cases, the map of variance (Figure 5.7B) demonstrates reasonably well defined borders between two nearby GP surgeries, again hinting at the existence of de facto market areas. The importance of certain GP surgeries to the local population is visualised by the mean direction of flow in Figure 5.7A when the local mean direction of flows around a GP surgery all seem to flow into that centre.

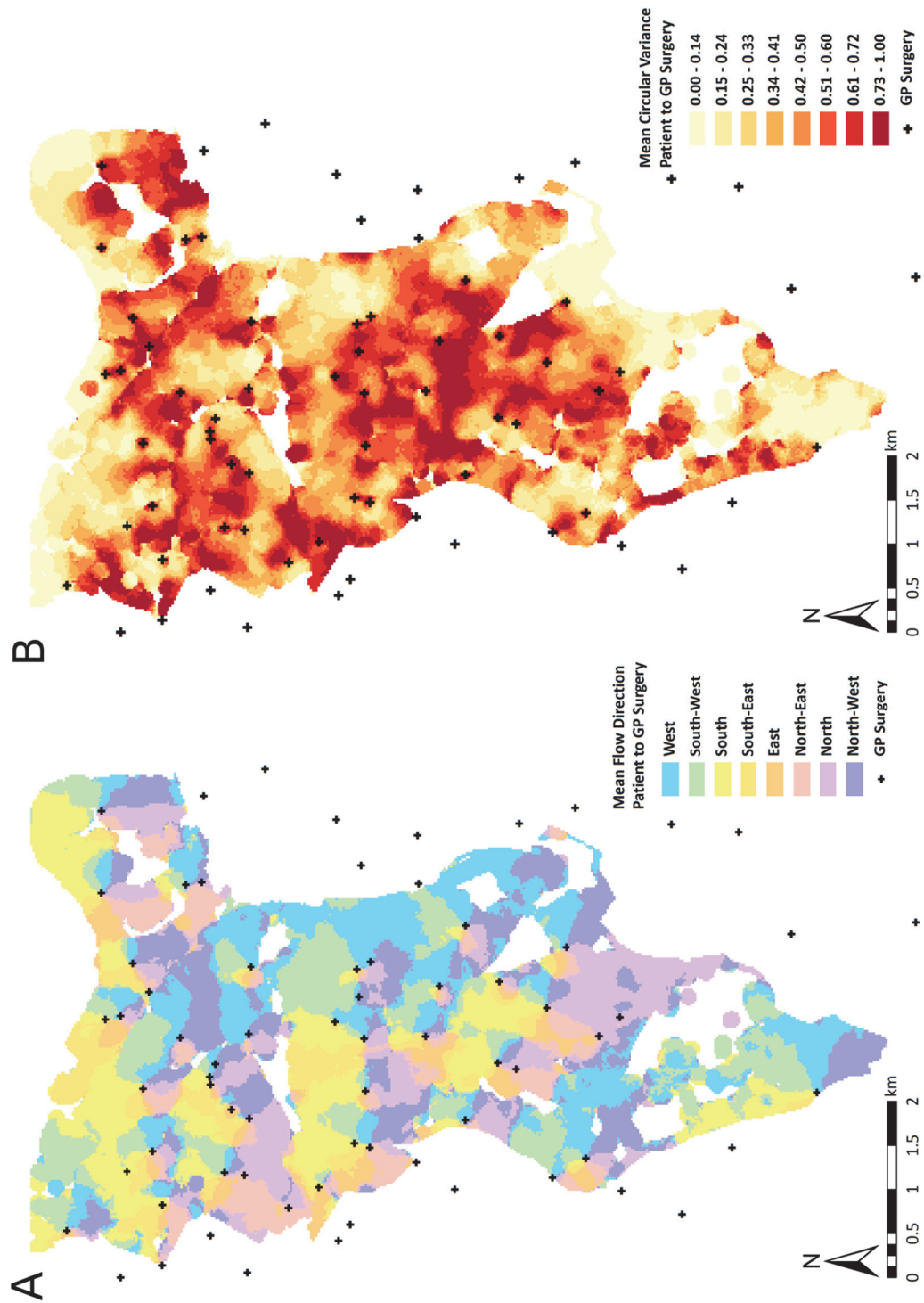


Figure 5.7: Mean flow direction (A), and mean circular variance (B) of registrations with GP surgeries, 100m bandwidth.

These descriptions of the system as a whole are useful in viewing how patients access care, and add to the understanding of “potential” considered in Chapter 3 by presenting a description of the actual situation. However, only by filtering the demand and supply of primary healthcare can a picture of provision begin to be formulated. The next section breaks down the patient population demographically using attributes in, or derived from, the Southwark patient register (Chapter 2).

5.3.3 Individual Patient Demographics and GP Surgery

Registration

The idea that different population groups have a differential potential to access local primary care provision has been discussed in Chapter 3. However capturing variation in potential is often different to observing it in reality. Similar to Table 5.1, the distance characteristics of different population groups can be tabulated and may reveal some tangible differences. Table 5.2 shows some difference between men and women in registering with GP surgeries: however, this is across the whole system of GP surgeries in Southwark, and the surgeries themselves are likely to have several GPs working in them. If differences do exist in registration with GPs for male and female patients it is likely to be an intra-surgery effect, and not necessarily related to distance. However, Tables 5.3 and 5.4, which show registration to GP surgeries by distance for patient age and Onomap-derived ethnicity, do seem to indicate some difference in registration behaviours by different groups of the population.

<i>Patient Sex</i>	N	Mean distance to nearest GP (m)	Mean distance to registered GP (m)	Median distance to nearest GP (m)	Median distance to registered GP (m)
Male	166,766	506.7	985.0 (1.9)	484.7	754.1 (1.6)
Female	158,498	508.2	987.6 (1.9)	486.4	758.4 (1.6)

Table 5.2: Distance to nearest GP surgery and GP surgery of registration by patient sex in Southwark (Ratio Registered:Nearest)

<i>Patient Age</i>	N	Mean distance to nearest GP (m)	Mean distance to registered GP (m)	Median distance to nearest GP (m)	Median distance to registered GP (m)
0-15	56,312	509.6	954.8 (1.9)	486.9	760.8 (1.6)
16-24	38,247	503.8	1020.9 (2.0)	491.5	751.5 (1.5)
25-34	77,483	503.4	922.5 (1.8)	481.6	705.6 (1.5)
35-44	64,384	504.1	966.9 (1.9)	480.7	746.9 (1.6)
45-54	41,505	509.2	1054.7 (2.1)	486.1	800.5 (1.6)
55-64	22,465	519.5	1079.4 (2.1)	495.6	822.2 (1.7)
65-74	12,473	515.3	1085.6 (2.1)	490.9	832.8 (1.7)
75+	11,302	516.0	1022.1 (2.0)	492.7	811.0 (1.6)

Table 5.3: Distance to nearest GP surgery and GP surgery of registration by patient age in Southwark (Ratio Registered:Nearest)

<i>Patient Ethnicity</i>	No. of patients	Mean distance to nearest GP (m)	Mean distance to registered GP (m)	Median distance to nearest GP (m)	Median distance to registered GP (m)
African	35,091	489.2	1138.7 (2.3)	467.3	770.1 (1.6)
British	166,058	515.6	979.0 (1.9)	491.8	773.8 (1.6)
E. Asian	9,451	513.3	1001.2 (2.0)	492.5	720.3 (1.5)
E. European	7,182	505.1	912.2 (1.8)	489.3	698.7 (1.4)
European	45,944	510.4	948.6 (1.9)	490.5	736.2 (1.5)
Hispanic	11,470	480.4	852.9 (1.8)	465.3	688.8 (1.5)
Muslim	31,263	484.5	958.5 (2.0)	464.0	737.9 (1.6)
S. Asian	6,012	542.6	1075.7 (2.0)	504.8	736.5 (1.5)
Other	12,793	501.8	973.7 (1.9)	485.0	723.7 (1.5)

Table 5.4: Distance to nearest GP surgery and GP surgery of registration by ethnic group in Southwark (Ratio Registered:Nearest)

In Table 5.3, there seems to be some basis for suggesting that increasing patient age is marked by a tendency to be registered with a GP surgery that is further away than might be expected given the proximity of the nearest GP surgery. Likewise, Table 5.4 indicates that some ethnic groups register with more distant GP surgeries than others. African patients are particularly noteworthy here, with the lowest average distance to their nearest GP surgery, and the highest average distance to their GP surgery of registration. Hays et al (1990) uses chi-square tests of independence, cross tabulating patient characteristics with the rank of GP surgery used, to assert significance to the different patterns of registration behaviour by groups of the patient population.

Table 5.5 suggests that there is a difference in the registration behaviours for men and women at the 5% level, largely based on slightly more men than expected using their nearest GP surgery, and fewer women. In reality it seems unlikely that this would translate to an appreciable difference.

<i>Patient sex</i>	GP Surgery proximity rank (1 = nearest)				
	1	2	3	4	5+
Male	66080	27193	16844	10491	46159
Female	62057	26301	15984	10038	44117

Table 5.5: Relative GP surgery registration: patient sex ($\chi^2 = 9.63$, $p = 0.047$)

The relationship between patient age and the rank of GP surgery of registration is significantly associated in Table 5.6, in particular the 25 – 34 age band has a strong tendency to register with the nearest GP surgery, and not with more distant GP surgeries, whilst all age bands greater than the 34 – 44 band tend to register less than expected with the nearest GP surgery, and more often with more distant ones.

<i>Patient age</i>	GP Surgery proximity rank				
	1	2	3	4	5+
0 – 15	21562	9709	5713	3512	15816
16 – 24	14851	6407	3711	2343	10935
25 – 34	34308	12760	7475	4739	18201
35 – 44	25927	10454	6607	4084	17312
45 – 54	14853	6623	4396	2686	12947
55 – 64	7989	3504	2366	1489	7117
65 – 74	4621	2149	1371	885	4540
75 +	4026	1888	1189	791	3408

Table 5.6: Relative GP surgery registration: patient age ($\chi^2 = 1989.71$, $p = 0.000$)

<i>Patient ethnicity</i>	GP Surgery proximity rank				
	1	2	3	4	5+
African	12424	5629	3291	1844	11903
British	64514	27361	17101	11062	46020
E. Asian	4046	1625	818	544	2418
E. European	3195	1207	666	470	1644
European	19002	7565	4689	2889	11799
Hispanic	4877	1945	1223	721	2704
Muslim	12128	5133	3171	1903	8928
S. Asian	2720	941	566	305	1480
Other	5231	2088	1303	791	3380

Table 5.7: Relative GP surgery registration: patient ethnicity ($\chi^2 = 1288.14$, $p = 0.000$)

A significant association is also shown between the rank of a patient's registered GP surgery and the ethnic group that patient belongs to. In particular, African patients tend to register with GP surgeries that are less proximal by rank, whilst patients from European, Eastern European and South Asian groups are more likely to use their nearest surgery.

5.3.3 Household Characteristics and GP Surgery Registration

Individual patients belong to households, and the composition of a household may have an influence on the GP of registration for members of the household. In Southwark, based upon the derivation of households discussed in Chapter 2, 60% of patients in the 74,803 non-single person households in Southwark use the same GP surgery. This breaks down by household occupancy rates as shown in Table 5.8

	Household Occupancy									
	2	3	4	5	6	7	8	9	10	11+
% Households using same GP Surgery	74.0	63.6	60.0	51.0	40.2	33.1	27.2	21.5	22.5	12.1
% of those Households using Nearest GP surgery	46.0	44.8	44.2	45.0	47.8	48.8	49.2	56.8	53.2	58.6

Table 5.8: Percentage of Southwark Household in which all members use the same GP Surgery

Households with lower total occupancies are more likely to use the same GP surgery as other members of the household than households with greater numbers of members. Further, within the households in which the same GP surgery is being used, the percentage for whom that GP surgery is the nearest is consistently higher than the rate of 40.0% for single person households, and the 33.0% for individuals who live in household that do not all use the same GP surgery. These trends suggest that there is a household effect in registration behaviours, and this can be further investigated using the classification of household lifestage derived for the Southwark patient register in Chapter 2 (2.3.9.2).

Class	Household Ref. Person Age	Composition	% Households using same GP Surgery	% of those Households using Nearest GP surgery
1	16 - 24	No dependent children	92.2 (64.2)	39.6 (43.1)
2	16 - 24	With dependent children	88.4	40.4
3	25 - 34	No dependent children	79.4 (59.6)	52.4 (60.0)
4	25 - 34	With children aged 0 - 4	78.1	42.9
5	25 - 34	Youngest child aged 5 – 10	80.8	43.4
6	25 - 34	Youngest child aged 10 – 15	72.0	42.7
7	35 - 54	No dependent children	72.1 (53.9)	44.7 (49.9)
8	35 - 54	With children aged 0 - 4	57.7	45.6
9	35 - 54	Youngest child aged 5 – 10	64.1	43.0
10	35 - 54	Youngest child aged 10 – 15	68.8	39.2
11	55 - 74	Single Person Household	100.0 (0.0)	34.0 (0.0)
12	55 - 74	2+ persons, no dependent children	61.9	41.2
13	55 - 74	With dependent children	41.5	43.2
14	75 +	Single person household	100.0 (0.0)	37.1 (0.0)
15	75 +	2 + person household	68.1	41.0

Table 5.9: Household lifestage classification and GP Surgery Registration (figures in brackets exclude single-person households)

Broadly speaking, the likelihood of a household having constituents that use the same GP surgery is higher for households which have a younger household reference person. Beyond this, there are few consistent patterns: households with dependent children seem less likely to have all inhabitants using the same GP surgery, although this might be explained by the fact that the single-person households will mostly be included in the “no dependent children” categories. When excluding single person households, for all age bands between 16 and 55, households with children are more likely to use the same GP surgery than households without children, but they are less likely to use their nearest GP surgery. This suggests two aspects to accessing care at the household level: firstly, that children’s choice of GP surgery is constrained by their parents – having a whole family use the same GP

surgery reflects a practical expedient of family life. Secondly, choice of an appropriate GP surgery may be more important than simply using the nearest one to the household, a GP surgery that is local to schools, for instance, may be valuable to family orientated households, whereas a single person household may place more emphasis on simply having a nearby GP surgery.

Finally, whether or not a patient lives in social housing was important to the potential to access a GP surgery in Chapter 3. The actual observed impact it has on registration is shown in Table 5.10. Regardless of whether single-person households are excluded or not, households which are socially owned and managed by Southwark council are less likely to be comprised of individuals registered to the same GP surgery, and in turn are less likely to use their nearest GP surgery.

	Household is Socially Owned (Managed by Southwark Council)	
	Yes	No
% Households using same GP Surgery	69.3 (56.9)	74.0 (62.0)
% of those Households using Nearest GP surgery	39.9 (43.2)	45.3 (47.1)

Table 5.10: Social Housing Tenure and GP Surgery Registration (figure in brackets excludes single-person households)

In light of the apparent differences in accessing GP surgeries across different characterisations of households, it seems unwise to discount household influences on patient registration behaviours. The final sub-section focuses on using the ACORN classification to consider neighbourhood-level effects in the patterning of GP surgery registration by patients.

5.3.4 Neighbourhood Geodemographic patterns in GP surgery registration

The ACORN geodemographic classification aims to simplify the complex socio-economic dimensions of small areas. The postcode level at which it is calculated can be seen to represent neighbourhoods to some extent, because postcodes in urban areas are largely indicative of the street, or estate in which someone lives. It creates a metric of similarity and difference through which to consider the neighbourhood circumstances of populations, highlighting areas which are likely have common circumstances and areas which may be subject to a different trajectory. If neighbourhoods are important in understanding peoples' behaviours (cf. Kawachi and Berkman, 2003) then geodemographic classification is an

organising principle under which to consider these different behaviours. Figure 5.8 maps the ACORN classification for Southwark, demonstrating the relative dominance of two groups in particular: those belonging to the “Urban Prosperity” class (yellow colours representing groups D, E and F), and those belonging to the “Hard Pressed” class (red colours; groups N, O, P and Q), but also the change in neighbourhood type in the Southern part of the Borough. Table 5.11 presents patient registration behaviours broken down by ACORN group.

Group	Description	n.	% Patients using Nearest GP Surgery	Mean Distance to Nearest GP Surgery (m)	Mean Distance to Registered GP Surgery
A	Wealthy Executives	1360	46.7	789.9	1445.3 (1.8)
D	Prosperous Professionals	11917	39.7	636.8	1234.4 (1.9)
E	Educated Urbanites	89125	43.7	524.3	962.5 (1.8)
F	Aspiring Singles	39326	36.2	532.5	1066.4 (2.0)
G	Starting Out	2673	39.3	618.1	1172.0 (1.9)
H	Secure Families	319	76.2	399.4	688.8 (1.7)
J	Prudent Pensioners	1016	52.4	508.3	875.4 (1.2)
K	Asian Communities	954	49.2	372.2	749.2 (2.0)
L	Post-Industrial Families	156	75.0	602.2	953.9 (1.4)
M	Blue-collar Roots	682	30.0	612.1	1133.2 (1.9)
N	Struggling Families	2459	41.8	594.1	1226.4 (2.1)
O	Burdened Singles	4830	29.3	597.9	1172.3 (2.0)
P	High-Rise Hardship	1184	28.0	444.5	1009.3 (2.3)
Q	Inner City Adversity	164634	37.4	473.8	949.2 (2.0)
U	Unclassified	4629	55.7	580.8	949.6 (1.6)

Table 5.11: Patient Registration by ACORN Group (Ratio Registered:Nearest)

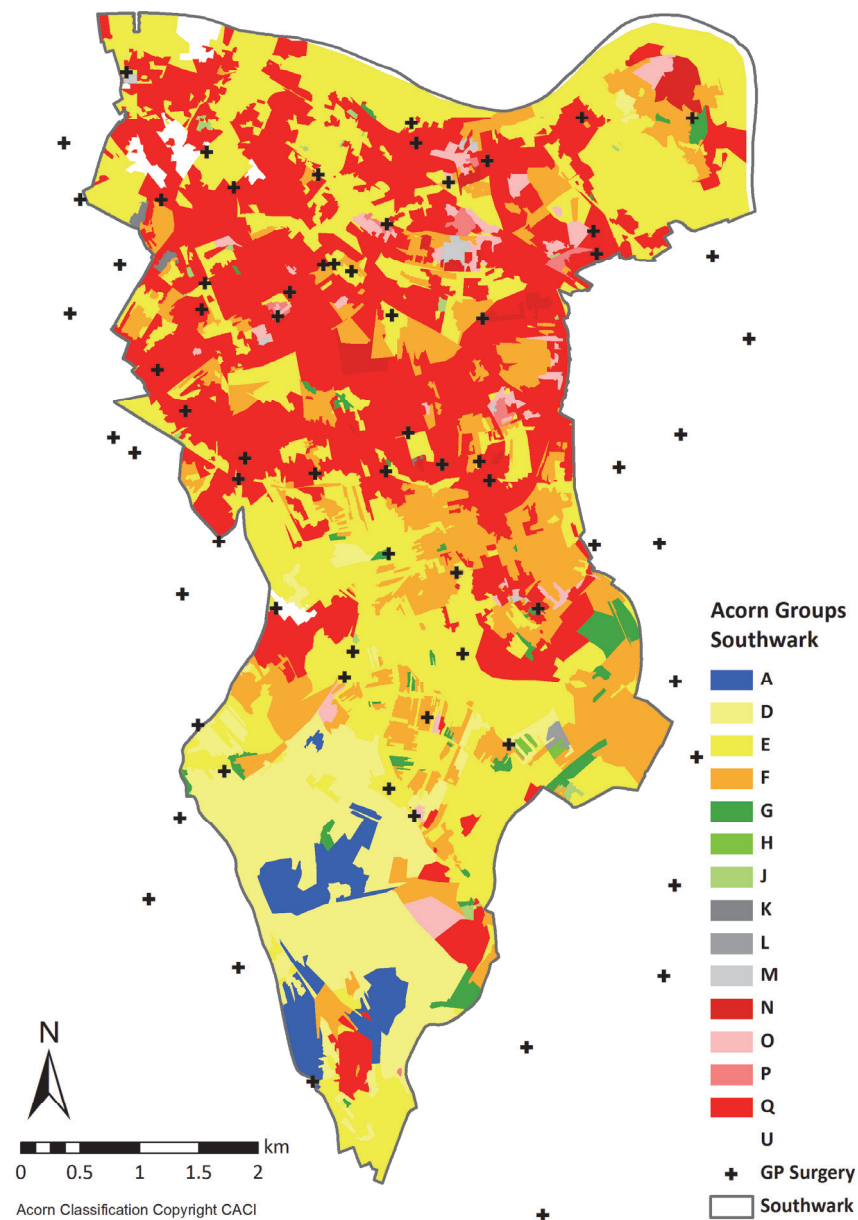


Figure 5.8: ACORN Classification at Group Level for Southwark, overlaid with local GP Surgeries.

5.3.5 Southwark GP Surgery Characteristics

Looking at the characteristics of patient registrations with GP surgeries gives some idea of the demand side of patterns of spatial interaction – how patient registration behaviours change subject to the characteristics of the patients themselves. However, GP surgery characteristics are also likely to influence a patient's choice of GP surgery. Unlike private healthcare systems in which an indicator of quality of care might play a role in patient choice, the NHS primary care system was created to provide equal access and quality to all; as such there are few indicators of the quality of a GP surgery in the NHS. A large amount of data on clinical care, organisational aspects, patient experience and other services is

collected by the NHS under the banner of "Quality and Outcomes". This data is itself one element of determining GP per capita payments, and the NHS awards financial incentives to GP surgeries that perform well on these measures. However, the NHS Information Centre states:

"The QOF (Quality and Outcomes Framework) only reflects part of the work that a general practice is responsible for, as such The NHS IC does not recommend or endorse the use of QOF data to rank practices into league tables." (NHS IC, 2011)

Indeed, the resultant QOF statistics show little variation in quality of GP surgeries across Southwark GPs, with the vast majority scoring above 90%, and all but 1 scoring above 85%, overall on the QOF assessment. What may be more valuable is an understanding of the GPs within the surgery, however, as GP surgeries are private bodies the NHS is not required to keep in depth information on the composition of the employees of a GP surgery. Therefore, data on GPs are compiled from the NHS Choices website, and the GP surgeries own websites where available; this enables a listing of the GPs working in Southwark GP surgeries, their sex, years practiced (which we assume is related to the actual age of the GP), ethnicity (derived using Onomap as for the patient register), and languages spoken. This is achieved by taking the reported GMC (General Medical Council) registration numbers for GPs, and searching them in the GMC GP database. There are 200 GPs in Southwark, of which 96 are male, and 104 female. In terms of ethnicity, the majority are British (45%), but a high number are South Asian or Muslim (16% in each case), African GPs account for 8% of GPs, whilst European and East Asian both account for 7% with Eastern European, Hispanic and Other groups accounting for 1% each. The average year of qualification was 1989, and making assumptions for the length of medical training this suggests that the average age of a GP in Southwark is around 45 years old. On average, a Southwark GP surgery has 4 ¼ GPs, and serves 6532 patients. The distribution of GP surgeries about this mean surgery size (4 ¼ GPs) is relevant to the previously discussed ordering of central places, operating under the assumptions of Central Place Theory we would expect GP surgeries that are larger than this mean to have a greater spatial influence, a larger market area, or as in Figure 5.6 a higher local value of percentage usage than GP surgeries than fall below the mean.

Initially, it is useful to consider the spatial patterning of usage of each GP surgery, so far the distance and travel time distributions have only been derived for patients accessing all GP surgeries as a whole (Section 5.3.2: Figure 5.2). The distribution of patients by each GP

surgery in Southwark is given by Figure 5.9, which visualises all 47 GP surgeries in Southwark, classifying registrations, which are aggregated at the OA level (c. 300 people per unit area), into deciles. It is clear from Figure 5.9 that each GP surgery has a unique spatial pattern of registration, and each demonstrates strong positive spatial autocorrelation, owing to the fact that GP surgeries are primarily location-based services. However, a GP surgery may be more similar in their spatial patterning to some GP surgeries than they are to others, which may reflect their position in a hierarchy of GP surgery Central Places.

In order to explore this further, we first consider how the different GP surgeries can be grouped subject to their patient distributions. A distribution of patients over distance, or travel time, as in Figure 5.2 can be generated for any given GP surgery, but to effectively group GP surgeries with similar distributions we need ways of summarising the characteristics of each GP surgery's particular distribution. Important descriptions of a GP surgery's distribution will include the mean distance that patients travel; the effective spread of patients around this mean distance; how bunched up (or skewed) the distribution is by distance towards the GP surgery location; and how smooth the distribution of patients is over distance, effectively how heavy the tails of the distribution are. Deriving a quantitative understanding of each of these characteristics of patient registration distributions by distance to GP surgery can be achieved by calculating the first 4 "moments" of each GP surgery's distribution. The moments of a distribution reveal something about the "shape" of a distribution, the moments used are thus the mean (5.5), Variance (5.6), Skewness (5.7) and Kurtosis (5.8).

$$\bar{x} = \frac{1}{n} \cdot \sum_{i=1}^n x_i \quad (5.5)$$

$$\sigma^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 \quad (5.6)$$

$$\gamma_1 = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^3}{\left(\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 \right)^{3/2}} \quad (5.7)$$

$$\gamma_2 = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^4}{\left(\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 \right)^2} - 3 \quad (5.8)$$

Having calculated the moments of the distribution of each GP surgery, a method is required that can group GP surgeries which have similar moments and hence whose patient distributions are similar, for this clustering is employed, the clustering method used was

Ward's clustering, which is an agglomerative approach to hierarchical clustering. This means that the procedure starts with a set of n clusters, each representing one observation, and it then iteratively joins the two clusters that are most similar until such a point as all clusters are joined into one cluster (5.9). Prior to the clustering procedure, the measures (Equations 5.5-8) are standardised using z-scores so that the magnitude of values for one measure does not result in it having additional weight in the clustering process than any other measure.

$$P_n, P_{n-1}, P_{n-2}, \dots, P_3, P_2, P_1 \quad (5.9)$$

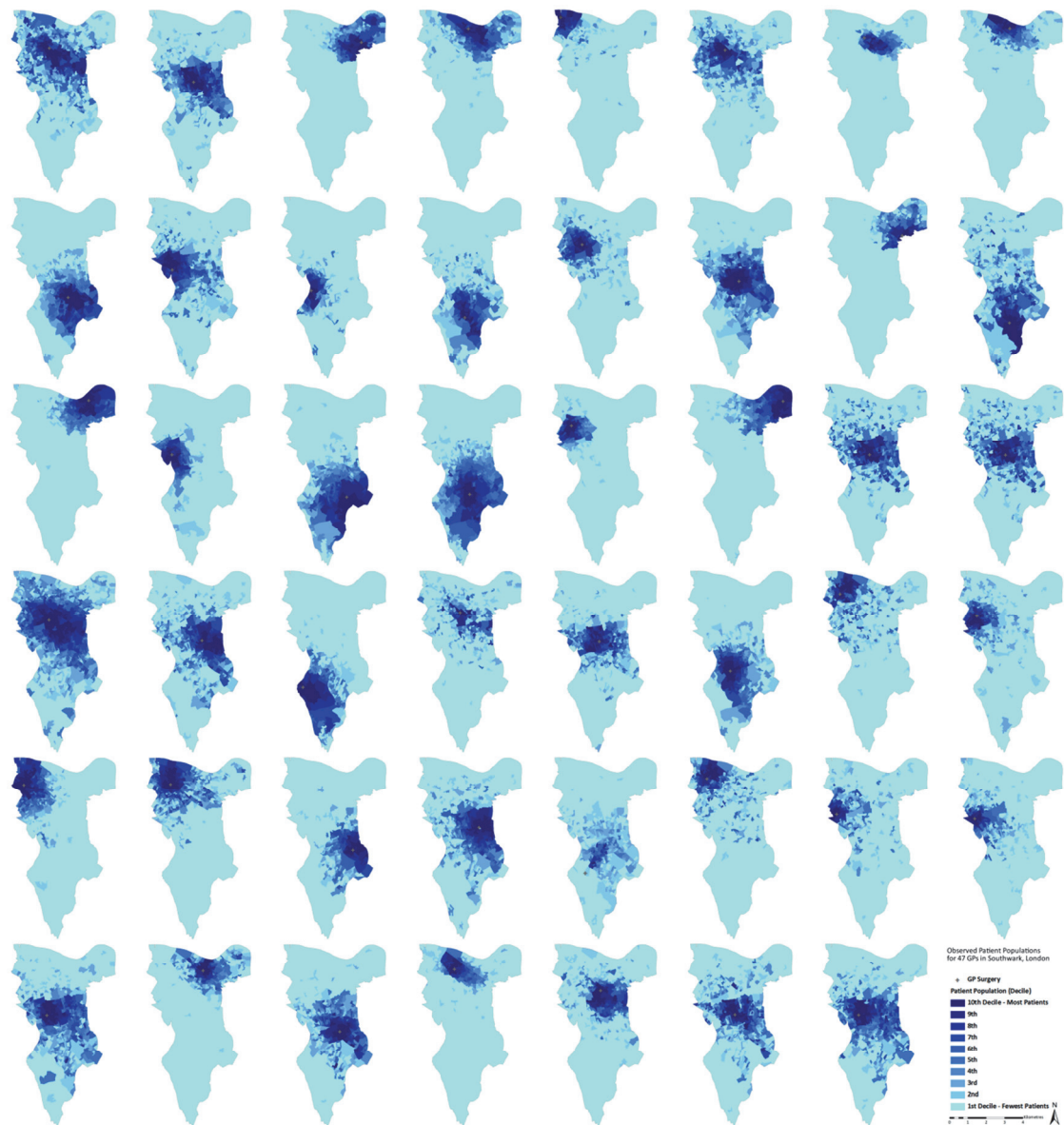


Figure 5.9: Patient Registration deciles for Southwark GP surgeries, patients aggregated to OAs.

The “distance” between each observation and every other is calculated using a distance metric and stored as distance matrix (or pair-wise vector). This effectively measures how different each mean, variance, skewness or kurtosis of each GP surgery is from all others,

creating a practical basis for distinguishing between more similar and more dissimilar GP surgeries. There are numerous choices for calculating a 'distance' between observations. Here a standard Euclidian metric (5.10) is used:

$$d_{xy} = \sqrt{\sum_i (x_i - y_i)^2} \quad (5.10)$$

In which the distance between observations x and y is given by the square root of the sum of the square of the difference between each variable i in observations x and y . It is also common to use the squared Euclidian distance, particularly on very large datasets where computation of the square root can take a comparatively longer time.

Clusters are formed at each stage by considering the 'information loss', essentially minimising the pair-wise distance, that would be caused by the joining of every possible pair of clusters, then the pair which causes the minimum possible loss of information (i.e. the pair with the lowest distance) is clustered and the algorithm moves to the next stage, repeating this again and again until a single cluster results. The clustering was performed for the measures (Equations 5.5-8) which characterise both the distance and time travel distributions of patients to Southwark GP surgeries. As is evident in the dendrograms shown in Figure 5.10 the clustering of GP surgeries by patient distributions differs depending on whether a network distance, or travel time metric is used.

The distance and travel time distributions of patients accessing a Southwark GP surgery (as in Figure 5.2) can then be recreated subject to the new aggregation of GP surgeries created by the clustering process, and visualised in Figure 5.10. "Cutting" the dendrogram, literally drawing a horizontal line across the dendrogram at a given value on the y axis, allows for different numbers of clusters to be specified. There are no specific rules that govern how this should be done, rather, a subjective appraisal of the dendrogram must be made, and a value chosen that is reasonable to the intended research. Figure 5.11 demonstrates that 3 clusters were selected for the network distance-based measures, and 4 for the travel time measures. Figure 5.10A shows that GP surgeries break down quite cleanly into 3 major clusters, however 4 clusters was taken instead for Figure 5.10B as to take three would leave one particularly large cluster, and 2 which are substantially smaller.

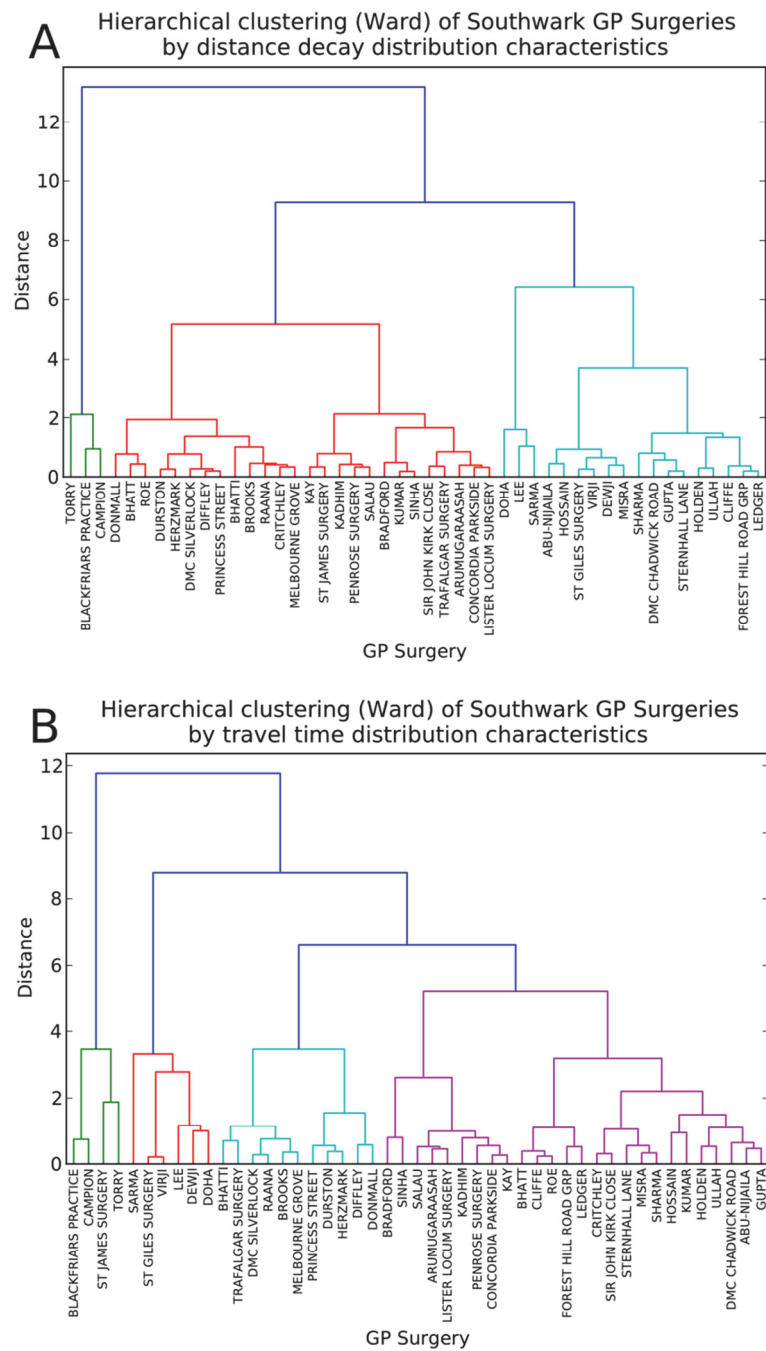


Figure 5.10: Dendrograms for clustering of distance (A) and travel time (B) distributions for patient registration with Southwark GP surgeries. (A) highlights 3 clusters, and (B) 4 clusters.

The distribution of patients to GP surgery by distance, subject to the clustering of similar GP surgeries, (Figure 5.11) demonstrates that the derived groupings of GP surgeries do have distinctly different patterns of patient registration. In Figure 5.11A, cluster 1 tends to have patient registrations which are more local to the GP surgeries in that cluster than either cluster 2 or 3; cluster 3 seems to have the least local registrations to GP surgeries on the whole. Similar conclusions can be drawn about the clusters in Figure 5.11B, however the

small numbers of GP surgeries per cluster has made for a less stable representation, highlighted by the spikiness of the lines, particularly cluster 2.

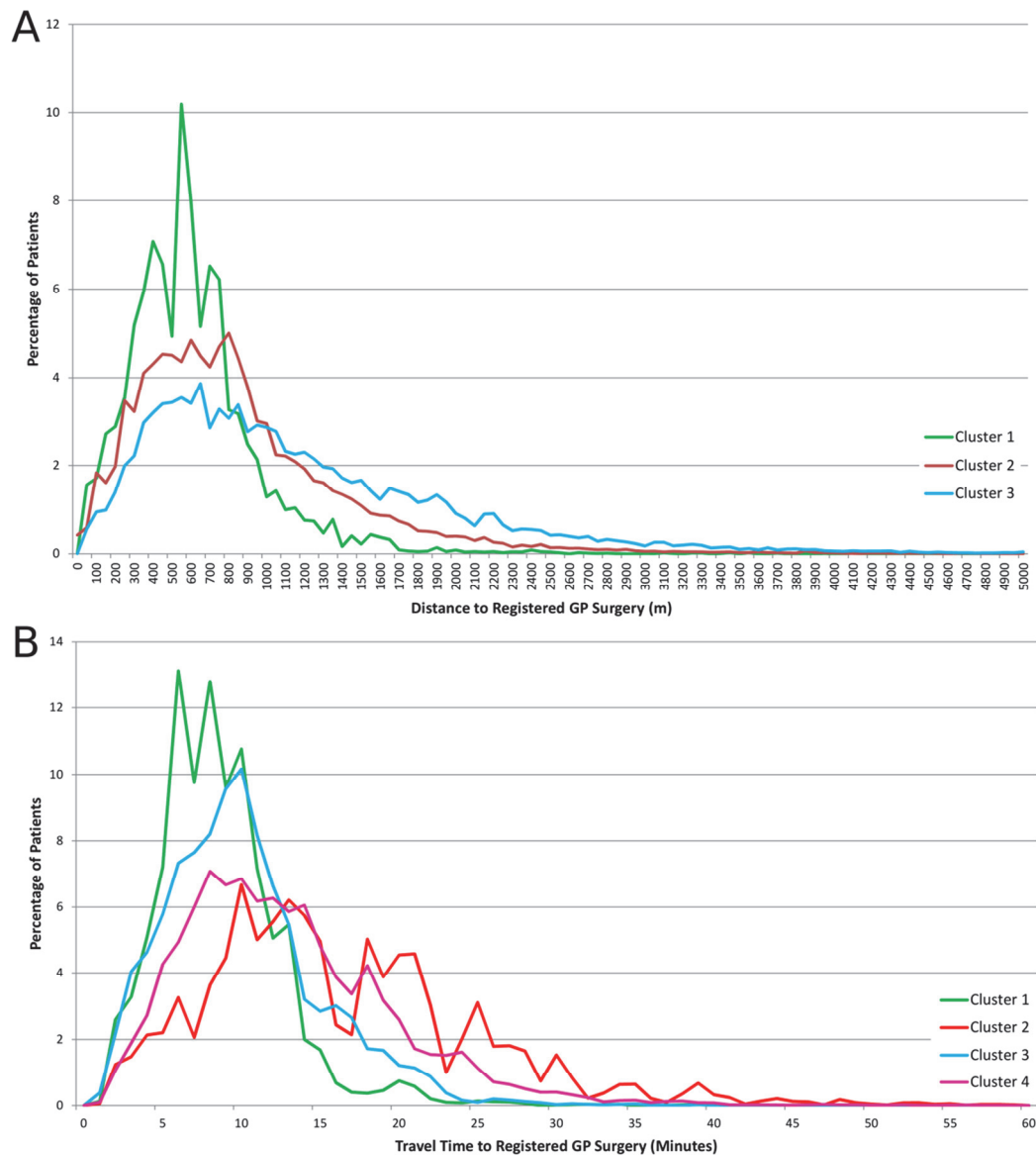


Figure 5.11: Distance (A) and time travel (B) distributions from patient to GP surgery by clusters defined in Fig. 5.10

The mean number of GPs working at GP surgeries in clusters 1, 2 and 3 of Figure 5.11A are 6, 4.5 and 3.66 respectively. Likewise, the mean number of GPs working at GP surgeries in clusters 1, 2, 3 and 4 of Figure 5.11B are 4.75, 2.2, 5.64 and 4.11 respectively. In general, the higher the mean number of GPs per surgery in each cluster, the more the patients belonging to GP surgeries in that cluster tend to concentrate locally with respect to registration distance to their GP surgery. Effectively, the larger the GP surgery, the greater influence it seems to exert over its local area, which supports the pattern of patient registration with the nearest GP surgery in Figure 5.6. This is again indicative of the

hierarchical effect of size in GP surgeries – larger surgeries are more attractive, and able to draw proportionally more patients from their local areas, whereas smaller GP surgeries lose out, and end up sampling their patient list from a wider area as a result – a finding not strictly congruent with Central Place Theory.

Clustering GP surgeries by the similarity of their patient registration distance, or travel time, distributions is perhaps overly simplistic. Whilst Figure 5.11 certainly seems to suggest that different groupings of GP surgeries exhibit different registration behaviours on the part of their patients, what we can actually infer from this is relatively limited. In order to address this, some additional characteristics of the GP surgeries themselves are introduced into the original clustering procedure, encompassing: the age, sex, and ethnicity of the GPs; and the size of the surgery, measured by number of GPs. Figure 5.12 shows the resultant dendrogram for the clustering procedure when this is undertaken; only the cluster output for network distance was used because the results for travel time were prone to creating many small clusters from which it is difficult to generalise useful GP surgery aggregation, as noted, this problem was also experienced previously in Figure 5.10B (in general this method would likely be more effective on a larger number of GP surgeries than the 47 in Southwark).

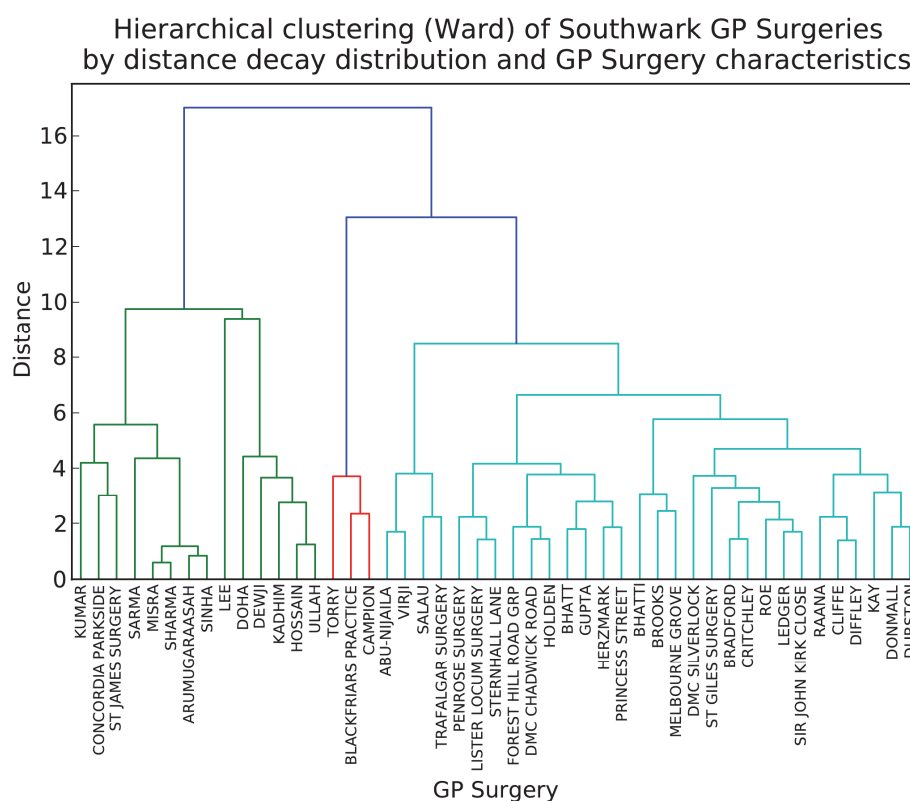


Figure 5.12: Dendrogram for Ward's clustering of GP surgeries in Southwark by GP characteristics and network distance distribution of registered patients.

Table 5.12 shows index scores for the different clusters of GP surgeries identified by Figure 5.12. An index score of 100 indicates that the variable in question represents the mean for all groups, whereas a score greater than 100 indicates a mean for that cluster that is higher than the mean for all groups, and vice versa for an index score lower than 100. The first cluster represents GP surgeries that are smaller than the Southwark average, which tend to be staffed by older, male GPs of Muslim or South Asian Onomap derived ethnicity; the second cluster is reserved for 3 surgeries which are very large, employing a large number of younger female GPs, many of whom are of British or European ethnicity; the third cluster is the largest consisting of GP surgeries that are average to large in terms of numbers of GPs employed, with no distinctive characteristics with regard to age and sex of GPs, although they are less likely to employ GPs of likely Muslim and South Asian origins.

Cluster	NumGPs	Female	Age < 45	AfricanGP	MuslimGP	SouthAsianGP	OtherGP
1	35.25	27.47	8.74	59.527	297.62	245.78	50.13
2	141	138.89	132.52	0.0	69.44	107.53	58.48
3	126.12	105.11	108.27	116.46	77.64	80.14	111.15

Table 5.12: Index scores of clusters (Fig. 5.12) by the input GP characteristics

These 3 clusters are used as a simple filter, and the patterns of patient registration belonging to each GP surgery cluster are assessed against what would be expected across the system of Southwark GP surgeries as a whole. Index scores for patient demographics (sex, age and ethnicity) are shown in Table 5.13 and 5.14, in which deviations from 100 indicate an over- or under- representation of the chosen variable in that cluster compared to the population as a whole.

	Sex (F)	Age 0 - 15	Age 16 - 24	Age 25 - 34	Age 35 - 44	Age 45 - 54	Age 55 - 64	Age 65 - 74	Age 75 +
1	97.00	102.37	100.46	94.38	99.51	102.14	100.55	115.99	98.77
2	99.36	69.05	97.24	133.15	107.29	84.38	91.59	82.43	96.22
3	100.70	102.30	100.15	98.20	99.44	100.95	100.64	98.16	100.61

Table 5.13: Index scores for clusters by Patient Characteristics (Sex and Age)

	African	British	East Asian	Eastern European	European	Hispanic	Muslim	South Asian	Other
1	152.05	83.77	96.67	91.53	90.72	99.04	143.89	84.79	109.04
2	60.85	108.07	98.38	101.07	117.35	90.34	75.74	144.61	88.57
3	92.38	102.75	100.86	101.72	100.42	101.08	92.78	99.22	99.10

Table 5.14: Index scores for clusters by Patient Characteristics (Ethnicity)

Table 5.13 demonstrates very little deviation from the population as a whole in terms of the sex of the patients accessing GP surgeries: however, it does suggest that younger adults are

more likely to use GP surgeries assigned to the second cluster, which is characterised by larger GP surgeries with younger GPs. There is also some suggestion that older adults, aged 65 – 74, are more likely to use GP surgeries in cluster 1. Table 5.14 shows some stronger patterns with regard to Onomap ethnicity, the first cluster of GP surgeries, which has higher numbers of Muslim and South Asian GPs in particular, and has larger numbers of registration by African and Muslim patients. Similarly, South Asian patients are more likely to use GP surgeries in cluster 2.

5.3.6 Consolidation

Exploring the patterns of patient registration with GP surgeries in Southwark using simple exploratory spatial data analysis tools reveals differential patterns of registration. Accessibility is shown to be a factor in this patterning, both in terms of distance and travel time using the public transport bus network. Further, it is likely that there are over-all effects on registration patterns, both in terms of the household and neighbourhood that a patient lives in. Finally, it is likely that the type of GP surgery that patients access has a significant effect on the registration behaviours of patients.

In the next section the composition of GP surgery patient registers is considered, comparing one that is normatively derived based on patient accessibility, with the actual observed registers for each GP surgery.

5.4 GP Surgery Composition in Southwark: A Normative Approach

5.4.1 Rationale

The previously articulated notion of normative accessibility, seen as the distance, or travel time, to the nearest GP surgery for any given patient, fails to account for constraints within the system. The key constraint to access in this case is that GP surgeries have a limited capacity – they cannot serve an infinite number of patients, rather their list size will reflect their ability to provide healthcare services to registered patients. In the event that a GP surgery reaches a level of patient registration that it considers to be an upper limit, the surgery can stop taking new registrations, effectively forcing local people who are unregistered to seek care elsewhere. This upper limit varies from surgery to surgery, dependant on the specific requirements and responsibilities of the GPs themselves, the

amount of part time work that “part time” GPs actually undertake, and the particular GP surgery’s attitude to using nurses – some employ a large number of nurses to provide straightforward services such as wound dressing, allowing the GP to focus on other patients, whilst other surgeries employ fewer nurses owing to space constraints or different care management attitudes.

Using numerical optimisation it is possible to compute an areal geography of access that minimises the distance, or time, that patients have to travel in order to access a GP surgery, subject to the constraint of GP surgery capacity. In effect this is a normative market area based singularly upon physical accessibility, and allows for the construction of a synthetic patient register for each GP surgery, in which each GP surgery is effectively a Central Place. Comparing the synthetic, accessibility optimised, patient register – the counterfactual – with a GP surgery’s observed patient register will allow the detection of non-spatial trends in patient registration behaviours. The expectation is that some GP surgeries will have patient registers that differ markedly from the synthetic, optimally generated register.

5.4.2 The Transportation Problem

Deriving accessibility optimised market areas for GP surgeries in Southwark can be achieved by solving a classic linear programming problem known as “the transportation problem”. The intent is to create a reallocation of people to GP surgeries based upon an ordering parameter – accessibility. Hay (1977) outlines the conceptual framework for optimisation problems, noting the level of detail to which constraints and assumptions in a given model need to be understood in order for a logically correct outcome to be achieved. Linear programming is the name given to a group of techniques for solving optimisation problems such as the transportation problem: in a sense linear programming constitutes a trial and error approach to finding an optimal solution in which a feasible solution is first defined, and then iteratively refined until it is clear that a “better” solution cannot be reached.

Cromley and McLafferty (2002) note that the transportation problem has often been used in health services research as an allocation tool for finding the optimal assignment of people or resources, when the locations of those people and resources, and of the healthcare facilities to which they are to be allocated, are fixed in space. As in this thesis, the normative allocation of people or resources is often used as a benchmark to understand a healthcare

system in practice, Mohan (1983) uses this approach to hospital location in North East England.

The approach taken in this research is to effect a reallocation of all patients in the Southwark patient register to best reflect an optimal allocation in terms of either distance, or travel time. The set of zones to be reallocated is based upon individual buildings housing patients, because this constitutes the smallest level of aggregation that also creates a spatial differential in distance to a GP surgery; it is often the case in Southwark that several households will be contained within a single building, giving each household effectively the same distance to travel to a GP surgery. There are 48,683 unique areal units representing buildings in the Southwark patient register; this may seem quite small as it implies that on average around 6 people live in each building, however as discussed in Chapter 2, around half of all addresses in Southwark pertain to flats, and a block of flats in the OS AddressLayer 2 counts as a single building, albeit a large one. The GP surgeries are those within Southwark, however, distinct GP surgeries that operate out of the same premises are aggregated. This is for the same reason that buildings are used as the level of spatial aggregation – the allocation of a demand unit to a supply unit becomes arbitrary if there is no distinction in the distance between demand and supply points. This reduces the number of GP surgeries in Southwark from 47 to 41. One further GP surgery is specified to represent the incidence of Southwark patients using GP surgeries outside of Southwark. GP surgery capacities are given by observed registration totals for each GP surgery, due in part to the difficulty of estimating the likely patient register size of any given GP surgery based upon the number of GPs they employ, and also because in terms of creating a counterfactual it is very useful if the number of patients in the observed patient registration data matches the number in the synthetic patient data. Optimal flows between patients aggregated to buildings, and GP surgery locations, using the transportation problem, is given by the following equation and set of constraints (5.11)

Objective function:

$$\min Z = \sum_{i \in I} \sum_{j \in J} d_{ij} x_{ij}$$

Subject to the constraints:

All patients must be allocated a GP surgery

$$\sum_{j \in J} x_{ij} \geq r_i \text{ for all } i$$

The capacity at a GP surgery cannot be exceeded

$$\sum_{i \in I} x_{ij} \leq q_j \text{ for all } j$$

No negative allocations allowed

$$x_{ij} \text{ for all } (i, j)$$

Where:

Z is the objective function, minimising travel time, or distance, of patients to GP surgeries.

I is the set of demand areas (buildings), where i denotes a particular demand area.

J is the set of supply sites (GP surgeries), where j denotes a particular supply site.

d_{ij} is the distance, or travel time separating demand area i from supply site j

x_{ij} is the number of people in demand area i assigned to be served at supply site j

r_i is the total number of people to be served at demand site i

q_j is the total capacity of facility site j to provide service

(Equation 5.11, cf. Cromley and McLafferty, 2002 p. 270)

Solving the transportation problem for the context specified is computationally intensive.

The solution was scripted in 64-bit Python and used the hugely powerful IBM ILOG CPLEX

Optimizer, which is specifically built to solve very-large problems.

5.4.3 Creating a Zonal Geography for the Southwark Patient

Register

The zonal geography to be created is based on the lowest level of spatially unique units in the Southwark patient register. In the case of the spatial referencing of the Southwark patient register, the reference data source – OS Mastermap AddressLayer2 – references spatially to the building level, and then subdivides those buildings into households. As such, a discrete point location exists for each building, and it is from this that distance or time travel is measured to each GP surgery; using this as the base level of geography in the transportation problem is advantageous as it removes the need to aggregate travel costs to a more general spatial unit, as well as minimising the number of people per areal unit, which lessens the possibility of multiple solutions of approximately equivalent optimality. As becomes evident in the execution of the transportation problem, the 48,683 demand areas by 42 supply sites is about the size that can be effectively handled on a powerful desktop computer, certainly the next level of aggregation (at household level) would not have been achievable using the equipment to hand.

Whilst OS Mastermap provides a set of building outlines that match the AddressLayer2 building centroid, they are not space filling. Ideally, a space-filling set of polygons will be used so that solutions from the transportation problem can be visualised to view the de facto market area in much the same way as Christaller visualises the geometry of market areas in Figure 5.1. To do this the Voronoi tessellation of the point set is computed.

The Voronoi tessellation, or Voronoi diagram, is a well-known method for deriving proximal polygons from a point distribution, and is the dual of the Delaunay triangulation (Worboys and Duckham, 2004). Any given proximal polygon in a Voronoi diagram has the useful geometric property that any point within that polygon is closer to the point that caused its generation than any other point in the observed distribution that led to the generation of the Voronoi diagram. Creating a geometric diagram of this size is problematic within contemporary GIS systems, again a programming solution had to be sought using 64-bit Python. The aggregated patient totals for the Voronoi diagram are given in Table 5.15.

Mean Population	Median Population	Minimum Population	Maximum Population	Standard Deviation	Mean Perimeter	Mean Area
7.01	3	1	1091	21.5	135.8 m	2232 m ²

Table 5.15: Descriptive statistics for Voronoi diagram derived building geography

As is evident in Table 5.15, the distribution of people by building is rather skewed, caused primarily by the existence of high rise estates which occupy very little physical space, but house many people due to their high density. It is possible that this will influence the outcome of the allocation, if areas with large populations have to be split owing to GP surgery capacities: however in the case of Southwark this does not emerge as a problem.

5.4.4 Representation of Market Areas for Southwark GP Surgeries

Visualising market areas for Southwark GP Surgeries is as straightforward as joining the optimal allocation output from the transportation problem to the computed building geography. Figure 5.13 visualises the optimal market areas for GP Surgeries based upon distance, and peak public transport travel time. There is little context given to the mapping so that the complexity of the output is appreciable: in each case a unique market area, representing the area best served by a single GP surgery premises in terms of physical access, is given a distinct colour so that it may be distinguished from the market areas of neighbouring, or proximal GP surgeries. The surrounding boroughs of Lambeth and Lewisham are included to demonstrate boundary conditions of patient registration.

The network distance-based approach (Fig. 5.13 A) demonstrates a relatively compact solution in most cases cleanly delineating a market area for each GP surgery, however the transport travel time market areas (Fig. 5.13 B) are somewhat more complex and fractured. The relative “roughness” of the travel time market areas is largely to be expected, as unlike distance which is distorted only by the structure of the road network upon which the

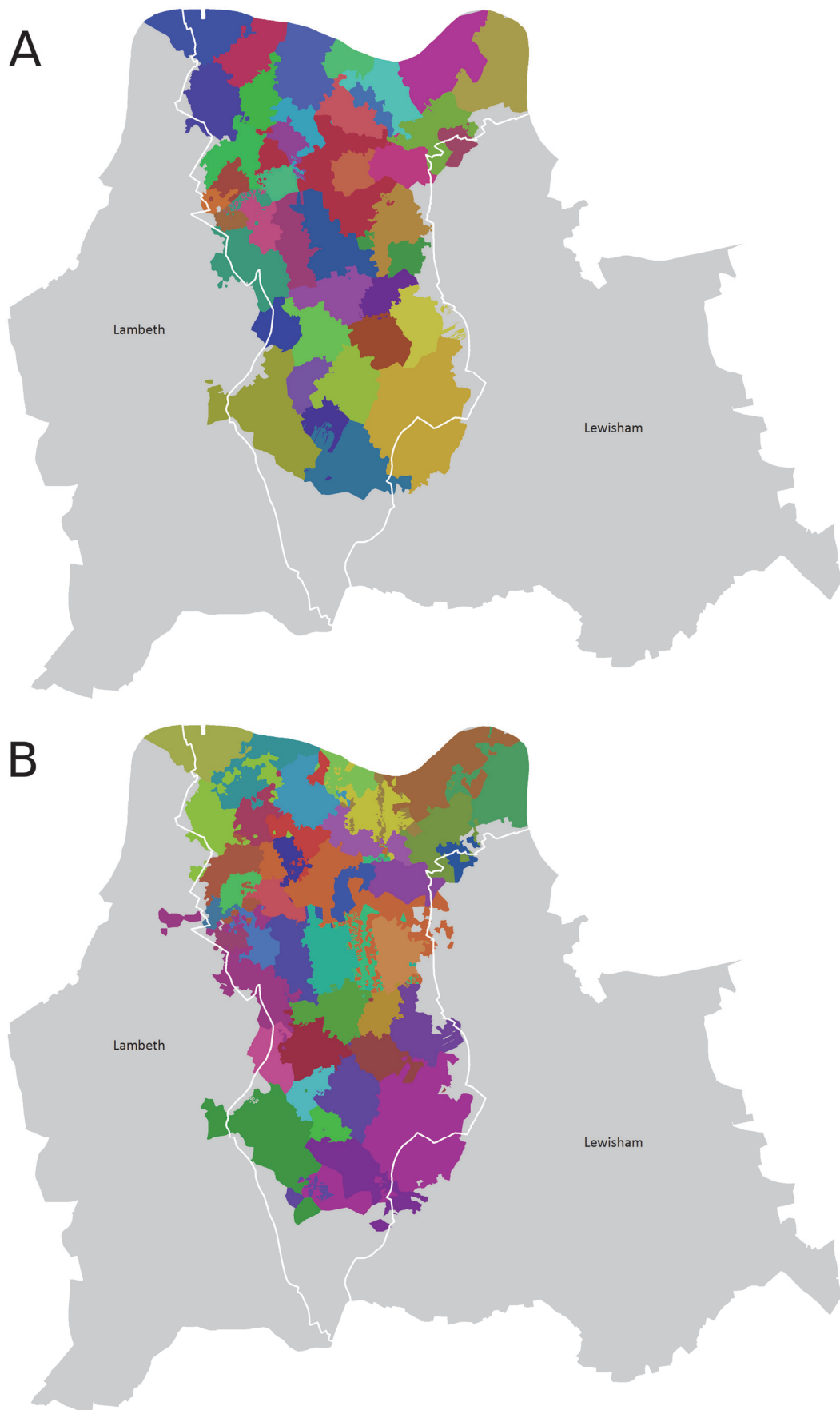


Figure 5.13: Visualisation of normative accessibility-based market areas for Southwark patients by (A) network distance and (B) Peak-time use of public transport.

measure is based, travel time is subject to the constraining effect of an incomplete network. Buses, although ubiquitous in most parts of London do not have complete coverage of the road network, nor do they give equal opportunities of access for all parts of the transport network in terms of waiting times, frequency or number of services, and bus stop locations. This means that areas which are different distances apart can have equal public transport travel times owing to the distortion of the public transport system that has been implemented. This is most notable in the higher population density areas of Southwark, where the contiguity of some market areas breaks down due to the patterning of public transport accessibility. Unlike the geometric regularity of Christaller's Central Place Theory hexagons, the market areas owing to different GP surgeries in Southwark are notably irregular, particularly in the case of the travel time derived GP surgery market areas. This is due primarily to the non-uniform distribution of population, and the imposition of distance upon a network, either by road, or including the bus network, which creates a non-isotropic basis for accounting for distance in the model.

In both parts of Figure 5.13, the differential availability of service owing to GP surgery capacity constraints and distance/travel time demonstrates the under provision of services in the southern part of Southwark. The subfigures both also show similar patterns of service along borough boundaries which raises an interesting issue; whilst the local NHS body responsible for commissioning primary care in Southwark is constrained to the borough boundary and as such provides care to Southwark residents, the Borough boundary itself is largely arbitrary, existing as it does in a continuously urban area. The GP contract that governs delivery of general medical services by GPs actually makes express provision of the requirement for GP surgeries lying on, or near, administrative boundaries to provide service to patients that could consider their GP surgery as local, even if they live in a different administrative area than the GP surgery itself.

The boundary effects owing to observed registration in Southwark are demonstrated in Figure 5.14. It is clear that there is a differential boundary effect dependent upon the availability of local provision inside and outside of the Southwark boundary. The western boundary with Lambeth is particularly rich in provision, creating stronger cross-boundary flows of registration than is evident to the east, where there are fewer local GP surgeries in Lewisham that are accessible for Southwark residents. Areas which have very limited within-

Southwark GP surgery accessibility, such as the south of the Borough have a high percentage of patient registrations serviced outside of the Borough.

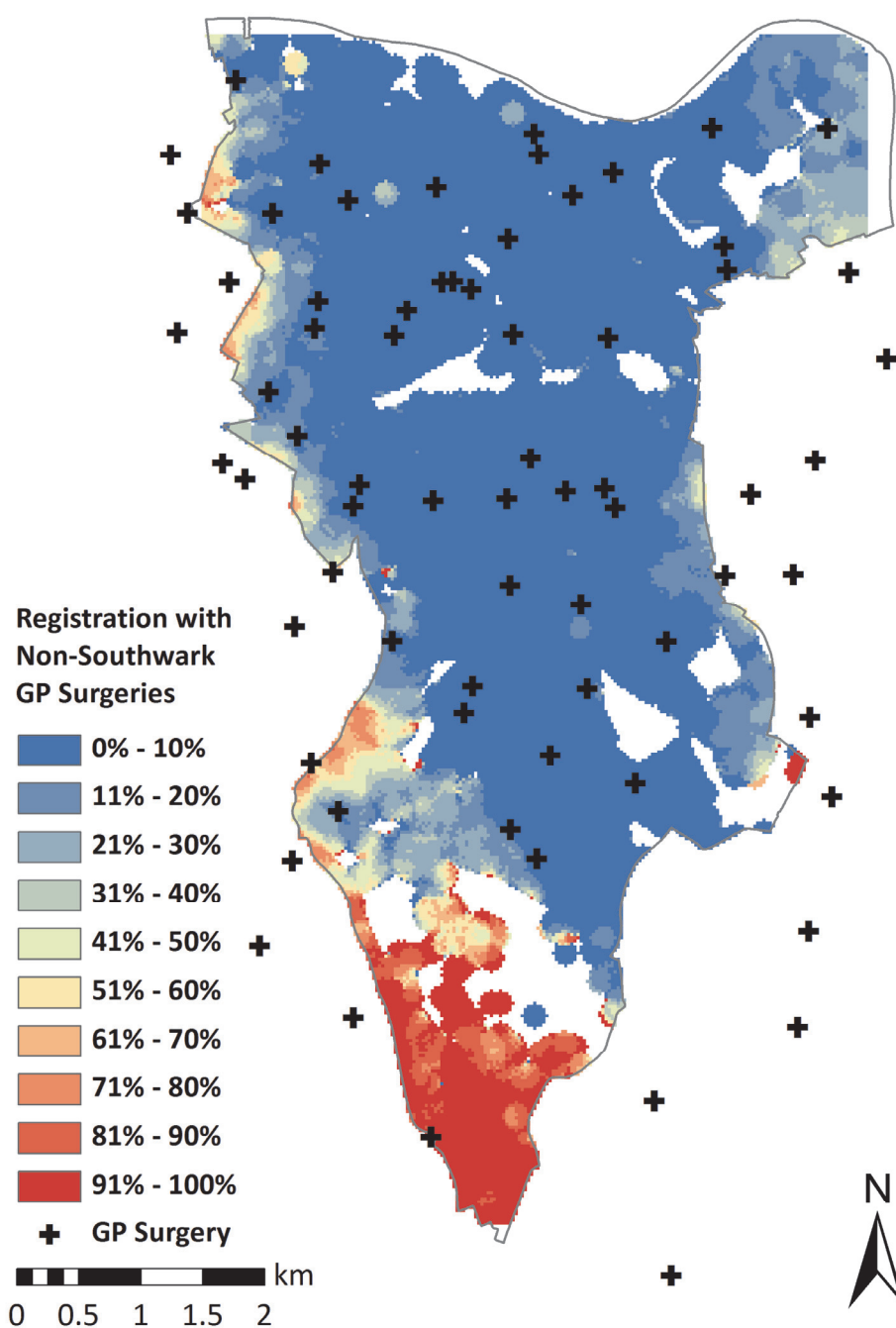


Figure 5.14: Percentage of Registration by Patients with GP Surgeries outside of the Southwark Boundary

Comparing the normative arrangements in Figure 5.13, which shows a westerly skew in normative market areas, with the evident boundary effects in Figure 5.14 it is possible to conclude that patients in the east of the Borough have a lesser opportunity to access local GP services than those in the centre or west of the Borough. Figure 5.7A has shown that the mean direction of patient flows along the eastern edge of the borough is westerly –into

Southwark, whereas the flows along the westerly edge are much more mixed and cross the Southwark boundary. On the whole, Southwark has a net out-migration of patients, with 34,568 patients leaving the borough to access general medical care from a GP surgery, whilst only 16,310 come into Southwark to use GP surgery services.

5.4.5 Analysis of Normative Market Areas

Boyce and Clark (1964) state that "shape has always been of concern in geography" (p. 561), and that it has particular relevance to describing physical features and urban form, as well as trade areas. The concern with shape in terms of trade areas stems directly from Central Place Theory in which a hexagon is the best regular space-filling approximation for a circle, and hence the most compact subject to the constraints raised. As has already been raised in considering the shape Southwark's GP surgery market areas: "It has been found that patterns of trade areas are far more varied and complex than had been postulated" (Boyce and Clark, 1964 p. 562). Differences in the relative shape of market areas for Southwark GP surgeries may have implications on the equitable provision of healthcare services as strongly irregular shapes may artificially limit the access for patients in some areas relative to others. This in mind, MacEachren (1985) considers the availability of shape measures for describing different aspects of shapes – "elongation, dissection, and compactness of regions, indentation of borders, sinuosity of linear features, and symmetry of networks" (p. 53) – focussing particularly on the compactness of geographic shape. Compactness is a characterisation of shape which seems particularly relevant to Central Place Theory, and to assessing the relative spatial inequity of different GP surgery market areas. MacEachren (1985) considers in total 11 different compactness measure specifications, including measures which favour area-perimeter ratios, deviation from a standard shape, such as a circle, and dispersion of elements from a centre point. In general, he finds dispersion measures to be the most effective compactness measure, particularly in local studies. Batty and Longley (1994) go further, suggesting that the shape of an area in terms of its perimeter-area relationship could be used to formulate a measure of compactness based upon space-filling fractals and demonstrate this for several urban examples.

In order to assess the difference between the distance and travel time derived representations of normative GP surgery market areas, firstly a simple compactness measure is used as a shape comparator, and secondly, an assessment of dispersion of patients about the GP surgery in each market area is considered. A fractal measure was not considered in

this case, but may represent an interesting direction for future research. The simple compactness measure used is the isoperimetric inequality, and is given by equation 5.12.

$$Q = \frac{4\pi A}{p^2} \quad (5.12)$$

The isoperimetric inequality is a ratio of the area (A) of a shape to its perimeter (p) that approaches 1 as a shape become more circular, in which a circle is understood to be the most compact shape. Thus it is an index of deviation from a standard shape (a circle with the same perimeter) under MacEachren's (1985) specification. The average Q for Southwark GP surgery market areas derived using network distance is 0.244, and for travel time is 0.155. This supports the earlier discussion of the "rougher" visualisation of travel time, effectively suggesting that the distance-based market areas are better approximations of a circle, and hence more compact.

The measure of dispersion used to measure shape compactness is given by MacEachren (1985 p. 57) who refers to it as "Relative Distance Variance" and attributes it to Bachi (1973), the specification of the measure is given by Equation 5.13. Despite the apparent simplicity of the relative distance variance, MacEachren (1985) suggest that it has the particular advantage of elucidating relevant insight into the specific distribution of a phenomenon within a shape, and hence is distinct to measures (such as Equation 5.12) which purely characterise the compactness of a shape based upon its geometry.

$$\text{Relative Distance Variance} = \frac{\text{Area}}{2 \cdot \pi \cdot (\sigma_x^2 + \sigma_y^2)} \quad (5.13)$$

where the variance in the x and y is the distance in x and y direction from the centre of the shape. Higher values suggest greater compactness compared to other areas.

As the areas in question are the market areas of GP surgeries, rather than define a centre, the GP surgery is used as the centre of its market area. In the case of the three GP surgeries that have multiple branches, the distance to the nearest branch was used in the calculation of variance. This is useful as the GP surgery may not be at the median point of the distribution of patients due to the constraints of allocating patients to GPs, incorporating this information into the measure will be important as market areas that are displaced in relation to the location of their GP surgery are less compact than those for which the GP surgery lies

at the median centre of the patient distribution. In a sense, a distributional justice is served if a GP surgery lies at the median centre of its market area.

The mean relative distance variance for market areas derived from the network distance is 0.96, this is more than the value for travel time derived market areas which is 0.86 suggesting that the network distance based transportation problem solution is more compact. Further, the standard deviation in compactness across market areas in the network distance-based model is lower, suggesting that compactness of market areas is more consistent in the network distance model than in the travel time model (network distance = 0.28, whereas travel time = 0.34).

Using the relative distance variance measure, the patient data can be disaggregated by patient characteristics to check whether the market areas are similarly compact for different population groups. Table 5.16 shows that there is very little difference in the mean compactness of market areas between male and female patients.

<i>Patient Sex</i>	Network Distance Model		Travel Time Model	
	Mean Compactness	Standard Deviation	Mean Compactness	Standard Deviation
Male	0.964	0.279	0.827	0.357
Female	0.955	0.279	0.832	0.351

Table 5.16: Compactness of Southwark GP surgery market areas using relative distance variance by patient sex.

However, if the compactness of market areas is disaggregated by Onomap-derived patient ethnicity, it reveals that African, East Asian, Hispanic, Muslim and South Asian groups tend to be more compact on average than British, Eastern European, European and Other groups when compactness is considered. This reinforces the results in Table 5.4 which suggests that the African and Muslim groups in particular are nearer on average, when considering unconstrained capacities, to a GP surgery than members of any other group.

<i>Patient Ethnicity</i>	Network Distance Model		Travel Time Model	
	Mean	Standard	Mean	Standard
	Compactness	Deviation	Compactness	Deviation
African	1.190	0.511	1.021	0.532
British	0.949	0.269	0.850	0.336
E. Asian	1.074	0.481	0.927	0.509
E European	0.968	0.306	0.869	0.410
European	0.968	0.287	0.860	0.362
Hispanic	1.000	0.331	0.924	0.400
Muslim	1.010	0.306	0.908	0.375
S. Asian	1.107	0.395	0.954	0.468
Other	0.957	0.289	0.900	0.414

Table 5.17: Compactness of Southwark GP surgery market areas using relative distance variance by patient ethnicity.

When the percentage of patients using the GP surgery of the market area which they lie within is considered, an increase is found for both network distance based, and travel time-based measures. Following Table 5.1, 39.2% and 36.5% of the Southwark patient population uses their nearest GP surgery as measured by network distance and time travel respectively, however when a patient's nearest GP is assessed in terms of the market area within which they fall, a percentage registration of 42.7% and 39.7% respectively is observed. This may simply reflect the particular pattern of population density and surgery location in Southwark, however the fact that the percentages of registration with the nearest GP surgery increases in the normative models may also suggest that the pattern of registration with GP surgeries by patients does to some extent reflect the constraints to registration imposed by GP surgery capacities and accessibility.

In order to probe the effect of market areas further, a synthetic patient register is created by linking patient records with the appropriate market area by way of a point-in-polygon operation. This allows an investigation of the patient characteristics of observed and normative registration patterns to be conducted. One notable advantage of this approach is that the total number of patients for each GP surgery seen in reality is preserved in the normative market area-based register. The Pearson Chi-Square Goodness-of-fit test is used to assess whether the observed numbers of patients is similar to that which we might expect given a patient register consisting of patients registering purely based upon a normative accessibility criterion. In Chapter 7, the normative models presented in this chapter are used in multivariate analyses.

For each GP surgery the following hypothesis is tested:

H_0 = There is no difference between the observed and normative distributions of a given patient characteristic.

H_1 = There is a different distribution of a given patient characteristic in the observed distribution compared to the normative model.

In the case of patient sex, for the 41 GP surgeries in Southwark, we accept the alternative hypothesis in 24 cases for the network distance-based and the travel time-based market areas. This indicates that the distribution of patient sex in 24 GP surgeries is unlike that which could be expected were patients to solely favour distance or travel time-based accessibility. In the GP surgeries where we accept the null hypothesis it may still be the case that differences may be observed in different patient characteristics, but it suggests that in terms of patient sex, the physical accessibility of a GP surgery is not a mediating factor. Patient age is grouped using the age bands seen in Table 5.3, and patient ethnicity as in Table 5.4, in both cases, all of the GP surgeries exhibit patient compositions that are significantly different from what would be expected given a normative arrangement. In general therefore, it can be concluded that factors other than the efficient spatial arrangement of patients are driving the composition of GP surgeries. This indicates that a large part of the patient population are exercising some form of behaviour, be it preferential behaviour, or as a result of an imposed constraint, when it comes to accessing care.

5.5 Consolidation

Defining a normative model based upon access to a GP surgery by either network distance, or travel time allows a set of market areas to be defined that delineates the pattern of non-overlapping, accessibility optimised zones for Southwark GPs. These market areas give an insight into the pattern of provision in Southwark highlighting a relative lack of service in the south of the Borough, and some suggestion of underservice along the eastern boundary. The notion that the composition of a market area would reflect that of the observed patient register for each GP surgery was pursued, and it was found that an approach that values accessibility solely is a poor fit for the observed pattern of patient registration with GP surgeries along the dimensions of sex, age and ethnicity. This lends credibility to the assumption that in an urban environment with a high population density, and a similarly

dense set of primary healthcare services, patients are actively trading off the effect of travelling small additional distances, or taking extra time, in order to access a GP surgery that is a better fit for their personal circumstances.

Mapping out the patterns of patient registration demonstrates that distance nonetheless does have a significant effect on registration. GP surgeries are after all location based services, which historically have set themselves a geographical constraint based upon the definition and maintenance of a prescribed catchment area. Areas that are local to GP surgeries, as in Figure 5.6, experience higher levels registration than those further away, something that can be seen in the directional pattern of flows to GP surgeries, and the variance in flow direction exhibited in Figure 5.7. The mapping of small multiples of surgery registration, as in Figure 5.9 demonstrates that each GP surgery does effectively have a market area. However these are not as rigorously defined as the market areas shown in Figure 5.13, or as is suggested would be the case by Central Place Theory.

Assessing the pattern of patient registration based upon the distances to the GP surgeries that patients use, and by creating a ranking of the GP surgery used, reveals that in addition to patient characteristics, household and neighbourhood contexts might be relevant to our understanding, as well as the GP surgery itself. In the next chapter, the definition of a market area is expanded, using ecological techniques to capture a “service area” for each GP surgery based upon the distribution of patient registrations which can overlap with other surgeries. It is suggested that this is a better analytical filter for profiling GP surgeries, within a context such as Southwark, than the more traditional normative model. This chapter, and the next, both of which aim to add insight into the interpretation of patient characteristics in accessing a GP surgery, are crucial to the formulation of a statistical modelling approach presented in Chapter 7.

6 Patient Characteristics and GP Surgery Service Areas in Southwark

6.1 Introduction

In the previous chapter, the basic behavioural characteristics with regard to accessing a GP surgery were uncovered for patients in the Southwark Patient Register. Subsequently, a linear programming approach was used in order to create a set of non-overlapping zones which represented a situation in which access to GP surgeries was optimised with respect to travel to a GP surgery, and the differences between the optimised population, and the observed population were analysed. However, it was also acknowledged that the pattern of registration using this normative method deviates significantly from the behaviours exhibited by patients in practice. This chapter moves beyond this theoretical approach, and seeks understanding from the actual pattern of patient registration itself. This is carried out by using the distribution of patients registered with each GP surgery to create a series of service areas that geographically bound prespecified proportions of registered patients. As such, the service areas are not defined in a normative way, as in the previous chapter, but in a way that accounts for the patterning of patient registrations with GP surgeries. Cromley and McLafferty (2002) refer to these as “natural” service areas. The composition of each GP list can be further investigated in the light of the service areas, which might be thought of as representing the specific “community” that each GP surgery is serving.

There has been much work on service areas in quantitative geography, with a wide range of relevant literature also referring to spheres of influence, market areas, trade areas and catchment areas, amongst other terms. However because the term “catchment area” has very specific connotations in the NHS, in order to distinguish between “catchment areas”, which are defined in by GPs themselves, the term “service area” is used here to denote the *de facto* service areas that can be generated from patient registration data. There is a fuller discussion of GP surgery catchment areas in the next chapter. This chapter begins by considering the literature relating to the definition of service areas of one form or another; several approaches are then considered as candidate methods for delineating service areas, before the one deemed most promising is used to assess the behaviour of patients in registering with Southwark GP surgeries.

6.2 Service Areas in Geographic Research

6.2.1 Background: Theory and Practice

The idea of a service area emerged from the work of Von Thunen (1783-1850) and Weber (1868- 1958), although they never formally articulated the service area idea as they were dealing with the locational behaviour of individual farms, or industries (Wilson, 2000). The nature of a service area implies competition by some measure, however the type of, or reasons for, competition will naturally vary according to the service being offered and the nature of the demand for that service. Competition, though, is key in deriving service areas, as the proximity of other service providers, and their characteristics, is what determines whether demand is satisfied by one service location or another. Early work centred around the term "market area analysis" with Wilson (2000) detailing the work of Palander (1902 – 1972) and Hoover (1907 – ? (Deceased, year unknown)) who focused on depicting market areas as isoline contours of cost or sales value. Putting aside the earlier theoretical perspectives, however, Applebaum (1965) traces the real practical insight into defining market areas to commerce, and store location research. The period of time prior to WWII (c. 1930s) in the USA is set as the most important developmental period for such research, with "empirical studies of store trading areas and on the market share" of "several leading grocery chain store firms" (Applebaum, 1965 p. 234) proving to be the driver. As Greenhut (1952) notes, the spatial configuration of the service area for any given service location will testify to the wisdom with which the service itself was located.

The geographic basis for a service/trade/market area is Tobler's First Law of Geography (Tobler, 1970), which demonstrates the importance of distance to the relationships between spatially proximate phenomena. However, early research into the field of retail market areas was supported primarily by "Reilly's Law of Retail Gravitation" (Reilly, 1931), which articulates trade areas in terms of "break points" between cities subject to the relative size of their populations. Batty (1977) notes that Reilly's law is one of the starting points for theories of gravitation in Geography and Social Science, and seeks to reformulate it in light of theories of spatial competition, and Central Place Theory as articulated by Christaller (1933) and Industrial Location Theory (Lösch, 1954) and considered in the previous chapter (5.2.2). Whilst there is a rich history of construction of market areas using spatial interaction models, it is not the specific focus of this chapter, suffice to say that such insights were important in the development of different attitudes and approaches to market area delineations.

Huff (1964) is one of the first outside of the “gravitationalists” to consider the geographical delineation of retail trading areas, and suggests a movement away from a generalised distance buffer approach to delineating trading areas, arguing that they may be subject to errors including differences with “transportation facilities, topographical features, population density, and the locations of competing firms” (p. 35). The position taken by Huff (1964) is focussed on the consumer, rather than the firm, creating probability surfaces for firms based on the behaviours of consumers with contours delineating equi-probability of customers visiting a given firm. Huff and Batsell (1977) later produced a model for defining market areas based upon the distribution of customer locations; they first rank customers cumulatively by distance from a firm and exclude those outside of a given cumulative percentage (Applebaum’s (1965) suggestion of 60-70% is cited), then those points are enclosed by a boundary line. Such a method is similar in character to taking a point-pattern and attempting to define its hull (Worboys and Duckham, 2004 p. 98), methods such as the envelope (bounding box), convex hull and alpha-hull have all been used to create service areas of increasing complexity. Unlike the central place, location-allocation, style analyses examined in the previous chapter, Huff (1964), and Huff and Batsell (1977) type service area delineations allow for the possibility of overlapping, or “congruent” (Huff and Rust, 1980), areas.

Overlapping service areas are an important development, highlighting the complexity of interaction between people and services, particularly at the local level. This is emphasised by Boots and South (1997) who sought to reformulate one of the traditional approaches to generating a space-filling, non-overlapping, set of service areas –the Voronoi diagram, which can be used to create unweighted service areas, or weighted areas based on the attractiveness of a service. Their revised model allowed Voronoi polygons to be created to represent services areas in which a customer can be assumed to select from amongst the k nearest most attractive services; such situations are similar to those experienced in primary care in urban contexts, where several proximal alternative GP surgeries might exist.

Indeed, whilst retail and commerce were certainly the early drivers of service area creation, and influenced the development of the myriad techniques for their creation, healthcare and epidemiology has since greatly influenced their usage and design.

6.2.2 Service Areas in Healthcare Analysis

"The *service area* or *catchment area* for a health care provider is the geographical area that contains the bulk of population served. For a health care provider, the service area ties the client population to a geographical area: a neighborhood; a community; or a set of communities." (Cromley and McLafferty, 2002 p. 249)

Service areas provide a framework for the provision of healthcare, viz. monitoring and management of health outcomes and health interventions, and can be used to assist the equitable distribution of patients, of resource allocations and of disease burden. Further, the rhetoric of healthcare in providing a location-based service has promoted the *de facto* existence of service areas through an articulation of community care, the provision of care to localities, and the suggestion that care be provided close to a patient's place of residence. Numerous schemes have been suggested in the academic literature, creating service areas for primary and secondary care services, as well as ambulance coverages, and service areas for particular disease sectors, notably cancer. The focus in this chapter is on primary care.

As has been suggested in previous chapters, and is discussed more fully in Chapter 7, the relevance of choice in UK primary care general practice was historically limited because of lack of differentiation in the services provided by different GP surgeries. However, as a more market-facing NHS developed, particularly in the late 80s and early 90s, with regard to competition between practice and greater patient choice, derivation and analysis of market areas began to proliferate. Martin and Williams (1992) detail a spatial interaction approach on this basis, suggesting that at that time "relatively little quantitative research has been directed towards spatial analysis of the primary health-care sector" (p. 1009). Bullen et al (1996) cite the movement to managing care in the NHS at the local level as underlying their derivation of "localities"- local areas for healthcare planning. Similar to the idea of a community, they argue that by basing healthcare on small areas that are recognisable to the public, "there will be greater public involvement in, commitment to and understanding of the disposition of health care resources" (Bullen et al, 1996 p. 801). Bullen et al's (1996) analysis also constitutes a significant endorsement for the use of GIS in healthcare planning. A similar method is investigated by Shortt et al (2005), who use regionalisation techniques to define non-overlapping catchment areas similar in conceptualisation to Bullen et al's (1996) localities.

Many concerns in providing equitable healthcare centre on access, a sample of which has been discussed in Chapter 3. In many of these instances distance or travel-time based service areas are computed: Shortt (2005) gives some examples but sees them as deficient to effective healthcare planning. Haynes (2003) states that “personal mobility is crucial in determining whether or not services can be reached” (p. 19), however, whilst defining a service area in this manner is ultimately very simple within a GIS, and offers a normative insight into equity, it contributes little to the understanding of a service area as such, because the pattern of access will not necessarily parallel the pattern of service choice in the population. Others prefer to think of market areas in terms of concentrations of opportunities (Whynes and Thornton, 2000) and offer indices in much the same way as spatial entropy was considered as a measure of ethnic mixing in Chapter 3.

However, given the nature of the Southwark patient register data, which is geocoded to patient residence, an opportunity to define a service area based on a dataset of unparalleled spatial resolution is offered. By and large gravitation, or spatial interaction, approaches require some kind of prior definition of a set of zones, and subsequently model flows of patients; this is counterintuitive as the Southwark Patient Register data already contains the flows, so modelling it in “what is” terms is somewhat redundant (although there would be value for “what if” questions). Equally, scale can be a problem in spatial interaction models; too many zones with too few people within them can increase storage requirements and computation times. Locality-based methods will create similar results as in the previous chapter, with non-overlapping zones defining a central-place-like market area for each GP surgery. As is demonstrated in the next section 6.2.3, the reality of patient registration in Southwark is suitably complex that overlapping catchments are necessary to capture patient registration behaviour. Models based on point patterns, such as Huff and Batsell’s (1977), or other shape-based hulls, are most interesting as they can take advantage of the Southwark Patient Data which is novel in its derivation of patient residential locations at the building level. Huff and Batsell’s (1977) model is limited though, as it cannot account for multi-nucleated service areas, such as might be the case for a surgery with several branch surgeries in different locations. The question of how a service area can be derived for a point pattern of patient locations that allows for the possibility of nucleation is considered after the next section.

6.2.3 The Context for GP Service Areas in Southwark

Southwark is an inner city urban environment with a dense population distribution and a high number of primary care GP surgeries, within a small area of around 30km². Such characteristics mean that patient behaviours with regard to registering with care are strictly different to those of patients in rural areas – oft studied for their constrained access to services. As the previous chapter introduced, patients are much more likely to use their nearest GP surgery if it is more proximal to them than other GP surgeries. However there is considerably more uncertainty if a patient lies roughly equidistant between several GPs, wherein they may trade-off lower distance to the nearest GP surgery in favour of another that fulfils a different role than simply being the nearest. In a sense, using a distance or time travel measure is too exacting, particularly when several GPs offer little difference in terms of nearness. For this reason this chapter considers the patterning and influence of overlapping catchment areas.

The importance of this consideration can be demonstrated using representation techniques that have previous been introduced (Chapter 3). In Figure 6.1A, the number of different GPs used by residents of Southwark is represented by way of a Gaussian kernel smoothing operation, demonstrating the increased propensity of people living in the centre of the Borough to use one of several possible GP surgeries. Similarly, in Figure 6.2B, the spatial entropy surface created in Chapter 4.3.3 is revisited, using registration with a GP surgery as the spatial categorical variable; the map suggests that there is likely to be registration with a greater number of different GP surgeries in the more central areas of the Borough. These findings tally with the expectations of service provision in Chapter 3.3.2, which demonstrates that the provision of service is highest in the centre of the Borough.

These representations lend weight to the idea that service areas in an environment such as Southwark will be best delineated as overlapping, in order to adequately manage the considerable complexity evident in patient registration behaviours.

In the next section, three methods for service area delineation about a given point pattern, are considered.

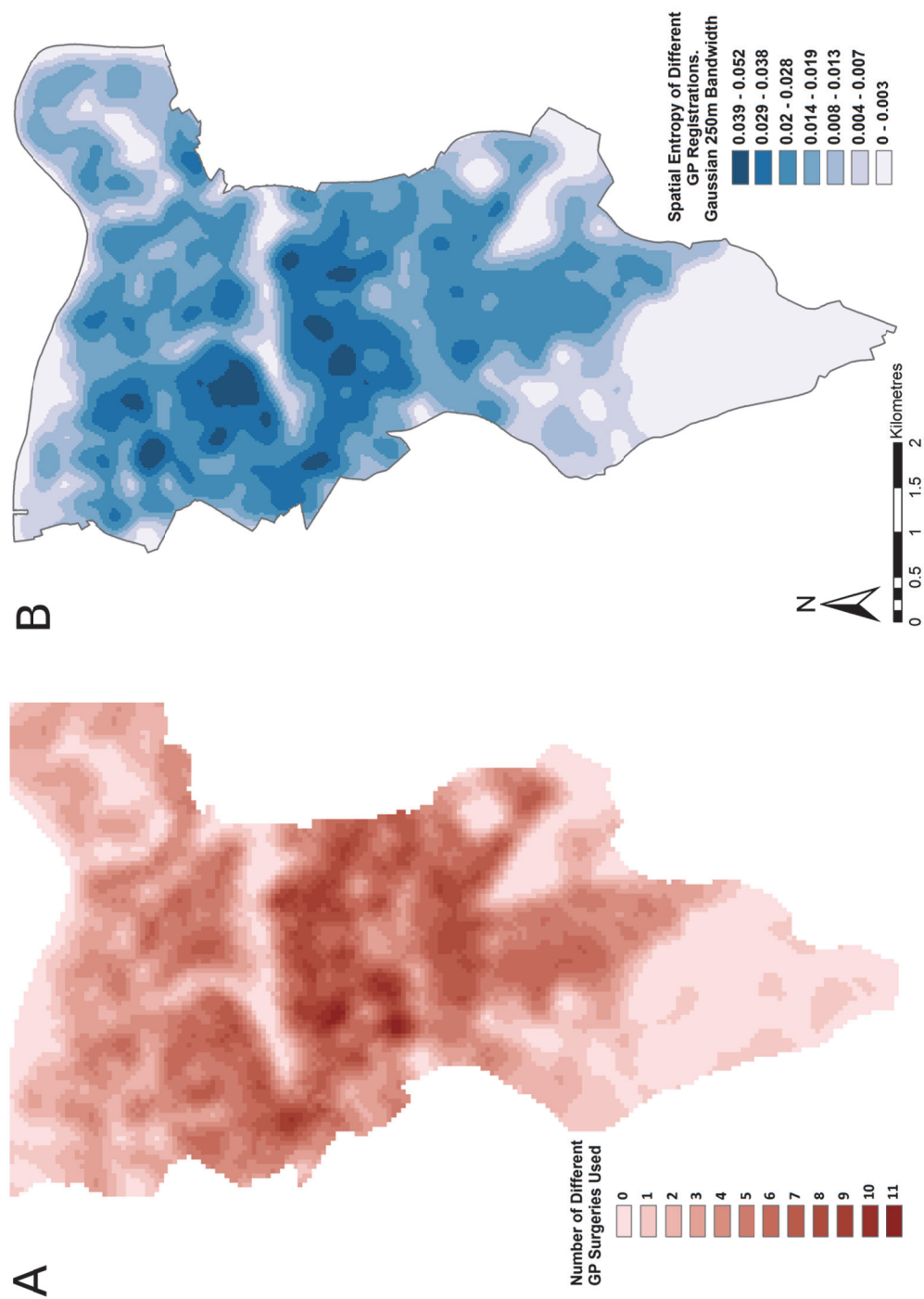


Figure 6.1: A) Smoothed (250m bandwidth) absolute number of different GP surgeries registered with B) Spatial Entropy of observed GP registrations.

6.3 Delineating Service Areas from Patient Residential Point Patterns

6.3.1 Home Ranges: an Approach from Ecology

The home range in Ecology is a long standing concept allied with the notion of an animal having a certain defendable territory. More than territory though, the home range is the “area traversed by the individual in its normal activities of food gathering, mating, and caring for young” (Burt, 1943 p. 351). Quite telling is Burt’s comment that “Home ranges are rarely, if ever, in convenient geometric designs” (p.351), an observation that may prove significant in the context of service area models. Home ranges are also commonly referred to in ecology as “utilisation distributions”, which bears out the behavioural element of patients registering with GP surgeries.

Home ranges are often calculated based upon animal tracking data, recently by using technology such as GPS, in any case, the location of an animal is sampled over time, with a single instance represented by a point in space. Collecting sufficient data allows for the utilisation of techniques which aim to delineate a boundary around the point pattern based upon the most frequently visited areas. Such attempts are similar to the Huff and Batsell (1977) method discussed, but greater development has yielded increasingly innovative methods for delineating service area-like polygons, these methods are of interest to defining service areas for healthcare from GP surgery patient registration distributions. Of interest in particular are 3 different approaches: Worton’s (1989) kernel methods, Kenward et al’s (2001) nearest-neighbour clustering, and Getz and Wilmer’s (2004) k-NNCH (k-nearest neighbour convex hull). As such, the exploration focuses on the three common methods for delineating an utilisation distribution: kernel methods, linkage methods, and shape methods respectively.

6.3.2 A Kernel Approach to Delineating Service Areas

Kernel density estimation (KDE) approaches to representing and viewing spatial information have been used in several chapters so far, including representation of accessibility in Chapter 3, and ethnic segregation in Chapter 4. However, specification of the KDE, and use from an analytical standpoint, has lacked a formal definition which is developed in this section using Worton’s (1989) insights into using KDE as a representation of home ranges. This method is

the only of the 3 tested that the author is aware of having been used in a social science context, with Gibin et al (2007) demonstrating the methods potential for defining GP surgery service areas.

6.3.2.1 Kernel Density Estimation

Kernel density estimation (KDE) is a procedure for estimating the continuous line (in 1 dimension) or continuous surface (in 2 dimensions) representation of a discrete set of points. De Smith et al (2009) describe the process whereby a kernel function (well-defined, smooth and optionally unbounded) spreads a point distribution, giving a greater weighting, in the context of the resultant continuous representation, to the centre of each point. In simple terms, KDE works by positioning a kernel (of, for instance, a normal distribution) with the central value (mean) over each point in the point distribution. The spreading of the point is defined by the width of the kernel, the bandwidth; in the case of the normal distribution this is contingent on the standard deviation which determines the slope of the curve. Adding all of the normal distributions positioned over each point and dividing by the number of points results in the probability density surface of the point pattern. The probability density surface is the surface that defines the likelihood of an observation occurring at any given point, the surface is usually represented by a raster grid of cells. Using KDE is particularly useful for spatially distributed data as it precludes making any explicit assumptions about the distribution of a point pattern itself – we have no reason to expect that a given point pattern follows a known distribution, and using an inappropriate distribution will result in misleading outcomes. The act of using sample data to estimate, for instance, the mean and standard deviation of a distribution assumed to be normal is effectively parameterising the expected normal distribution; as KDE does not parameterise in this way it is said to be non-parametric (Burt et al, 2009). According to Burt et al (2009, p. 416-7) the KDE probability density surface of a point pattern, estimated on a grid, is given by:

$$\hat{f}(x, y) = \frac{1}{nh^2} \sum_{i=1}^n K\left(\frac{d_i}{h}\right) \quad (6.1)$$

In which K represents the kernel function used, h is the bandwidth, which controls the effective spread of the KDE, n is the number of data points, and d_i is the distance between the cell (x,y) for which the probability density is being estimated and a point in the point pattern. There are numerous different kernels (K) that can be used: de Smith (2009) lists 6

popular alternatives including the normal and Epanechnikov which are most interesting in this context. The normal kernel is given as:

$$K(t) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) \quad (6.2)$$

And the Epanechnikov function is:

$$K(t) \begin{cases} \frac{3}{4}(1 - t^2), |t| \leq 1 \\ 0, t > 1 \end{cases} \quad (6.3)$$

In which, in both cases:

$$t = \frac{d_i}{h} \quad (6.4)$$

In previous chapters, the unbounded normal distribution has been used as the kernel, largely because it is straightforward to implement it using the Python SciPy “GaussianKernel2d” function. In using KDE to estimate service areas (and in Chapter 3, to estimate spatial equity) the Epanechnikov function is used. This (bounded) function is used largely because ESRI’s ArcGIS 10.x implements KDE with Epanechnikov and it has also been suggested that the kernel has a useful property that makes it the optimal choice for KDE. The performance of a kernel is measured by the AMISE (asymptotic mean integrated square error), a measure of the global error, and the accumulated point-wise error, and it has been found that the Epanechnikov kernel minimises this (Scott, 1992). The effect of the different kernels is to change the way data is aggregated, with a normal kernel producing a slightly smoother representation than an equivalent Epanechnikov kernel. However, Härdle et al (2004) “conclude that for practical purposes the choice of the kernel function is almost irrelevant for the efficiency of the estimate” (p. 61), so the variation in kernels used in this thesis should have no practical significance on the veracity of the results obtained.

6.3.2.2 Bandwidth Considerations

Key to successfully using KDE to visualise GP service areas is setting an appropriate bandwidth. In previous chapters this has been overlooked to some extent as it was claimed that in such circumstances bandwidth had more to do with a theoretical reasoning of the size of a community or neighbourhood than it did with fixing a bandwidth that was representative of the point pattern itself. However, in this context it becomes important to extract a useful surface that is related to the character of the underlying data points, and for

this a consideration of how to set an optimal bandwidth is important. This is achieved using the normal optimal smoothing equation given in Bowman and Azzalini (1997), adapted for use with an Epanechnikov kernel due to Silverman (1986 p. 86):

$$h = 1.77 \left(\sigma n^{-\frac{1}{6}} \right) \quad (6.5)$$

σ is the standard deviation, a measure of spread of data based on the normal distribution, however, as has already been suggested, this may be an incorrect assumption in the case of spatial data. Thus, Bowman and Azzalini's (1997) suggestions of the use of the measures of average, and median, absolute deviation (AAD (equation 6.6), and MAD (equation 6.7)) are also investigated:

$$\sigma = \text{mean}(|x_i - \text{mean}(x)|) \quad (6.6)$$

$$\sigma = \text{median}(|x_i - \text{median}(x)|) \quad (6.7)$$

The key outcome for the bandwidth setting is that a surface is created that is neither over-, or under- smoothed. Oversmoothing is the characteristic of a probability surface having indistinct features due to the excessive smoothing, whilst undersmoothing is the characteristic of that same surface being too rough and granular. The goal is therefore to find a bandwidth that strikes a balance between over generalisation and discretisation of the point pattern. This is illustrated for the pattern registration distribution of a GP surgery in Southwark in Figure 6.2. The selection of the bandwidth, contingent on the measure of spread used, is subjective; the average absolute deviation measure has been chosen because it seems to be the most effective of the three candidates. In the case of standard deviation, the extreme outlying values in the distribution artificially inflate the size of the bandwidth; conversely the median absolute variation sets the bandwidth too low, so the less dense non-central areas of the distribution rapidly become too discretised leading to the presence of numerous small islands; the average absolute deviation appears subjectively to be a happy medium of these two propensities.

Other authors have suggested that optimal bandwidths can be computed using least squares cross validation (LSCV), in which the data are partitioned into a training set and compared to a validation set to find a value for the bandwidth which maximises the cross validation score. Brunsdon et al (1996) discuss the deployment of this method in Geographical Weighted Regression (GWR), local regression and KDE.

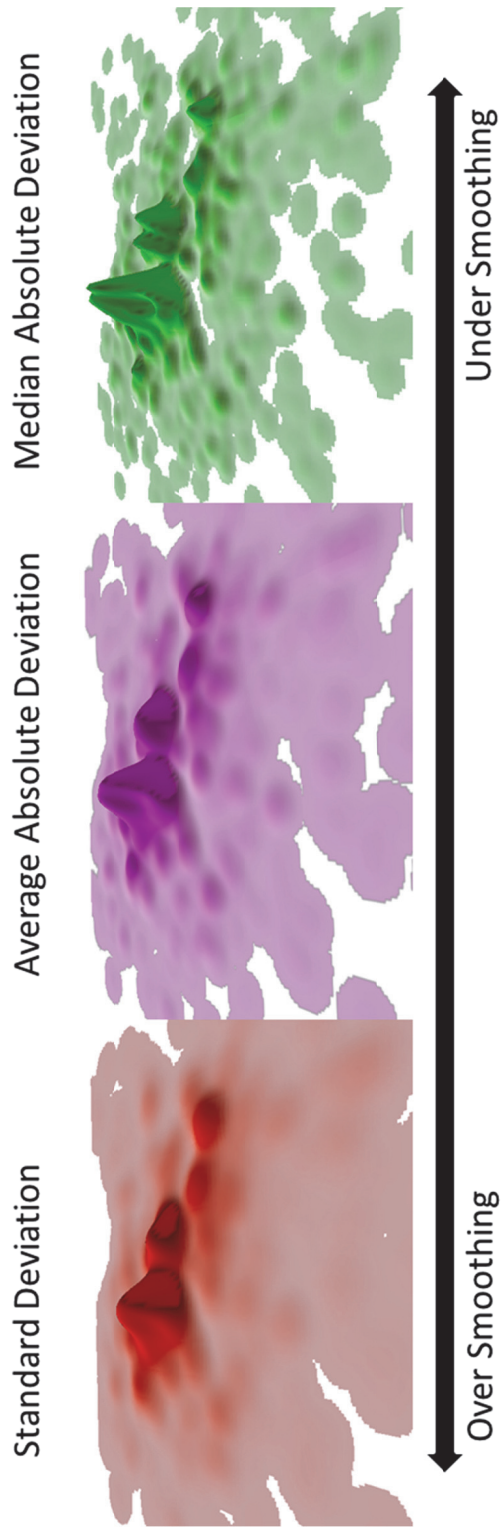


Figure 6.2: Bandwidths specified using different measures of spread for patient registration with a GP in Southwark. Linear extent of each image approx. 6km.

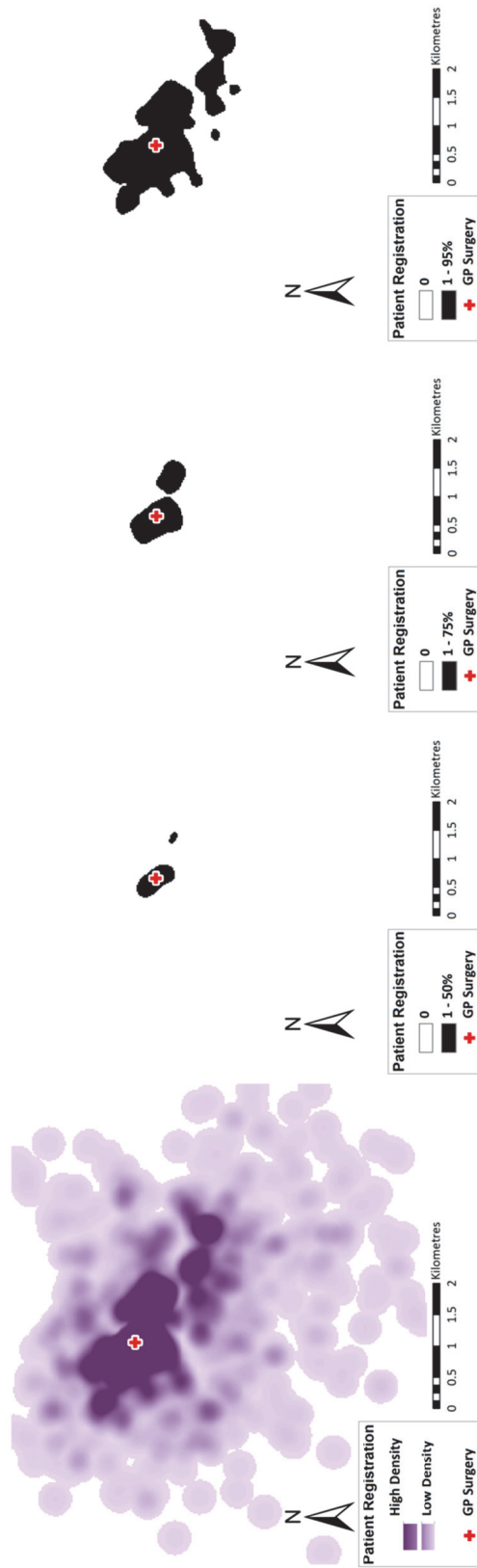


Figure 6.3: Thresholded rasters, prior to contouring, demonstrating spatial extent of 50%, 75% and 95% service areas for the GP surgery in Fig. 6.2.

Testing the influence of LSCV reveals little in terms of difference for selected bandwidth, and increases the computation time for creating a KDE surface. The same is true of the associated practice of using variable size kernels depending on the local diffusion of point data, however, this requires local estimation of bandwidth which adds to computational time, and adds to the practical uncertainty of the subsequent method of delineating a service area from the density distribution by creating a surface composed of inconsistent size kernels, and hence differential rates of smoothing. Kenward et al (2001) suggest that LSCV methods are most useful when dealing with a diffuse point pattern, a situation contrary to the well-defined clusters in evidence around GP surgeries. In principle, the LSCV technique does nothing to detriment the KDE process as used in this context, and its application would not be viewed as inappropriate, however, the fixed kernel approach, using a bandwidth derived using an average absolute deviation measure of spread is effective and fit-for-purpose and poses far fewer computational challenges in achieving a broadly similar outcome.

6.3.2.3 Percent Volume Contours

Having defined an appropriate KDE surface for a point pattern, a service area can be defined by encapsulating a pre-defined percentage of that surface based on the cumulative ordering of cell values from high to low. This allows a contour to be drawn within which it would be expected that at least a given percentage of the point pattern would fall, although in practice it can work out that slightly more points fall inside the contour due to the effect of the spreading of the actual observed distribution, or errors associated with rounding of cumulative percentage figures. The term "volume" is used because, as in Figure 6.2, the output KDE raster surface can be seen as having a volume (edge length squared x cell density value) and hence can be represented arbitrarily in 3 dimensions. The percent volume contour can be calculated in the following way, having computed a KDE raster surface:

- 1) Compute the proportion of the whole volume of the raster contributed by each cell.
- 2) Sort the raster from high volume to low volume.
- 3) Recode cells as 1 until a given cumulative percentage volume is reached, thereafter recode cells as 0. This creates a binary raster.
- 4) Contour the raster, and convert to a polygon to enable service area analysis.

This method allows the creation of polygons which can be used to query the patient contribution of a GP surgery's service area. Figure 6.3 shows what this looks like in practice.

6.3.3 A Clustering Approach to Delineating Service Areas

A cluster linkage approach to estimating home range is suggested by Kenward et al (2001) that offers some interest to the delineation of service areas. The method distinguishes itself by using nearest-neighbour distance within the point pattern, allowing the possibility of creating multinuclear services areas, similar to those in evidence in the KDE method considered. On this basis, the nearest-neighbour approach is preferable to the minimum distance to a centre/facility approach adopted by Huff and Batsell (1977). The key practical distinction between this method and the previous KDE-based method is that it employs no smoothing, working directly with the discrete point pattern.

6.3.3.1 Modified Single Linkage Clustering

Single linkage (A.K.A. nearest neighbour or shortest distance) clustering works on the basis that points in a distribution are incrementally joined in a way that minimises the mean joining distance. Interestingly, this method of clustering parallels the minimum spanning tree (MST) method of Kruskal discussed in Chapter 4, albeit placing importance on the exact order of the clustering which is irrelevant to MSTs (Gower and Ross, 1969). Single-linkage clustering is a hierarchical technique that first identifies each data point as a single cluster (known as a singleton node), then successively merges these singleton nodes until such a point as all singleton nodes belong to one cluster, this is known as agglomerative clustering (Everitt et al, 2011). The criterion for merging is that at each step the two clusters (A and B) whose two nearest members (x and y) have the smallest distance are merged, this is represented as:

$$\min \{d(x, y) : x \in A, y \in B\} \quad (6.8)$$

The distance between x and y can be represented in a number of ways, although in terms of defining a service area it is the actual geographical distance between point observations that is important. In theory this could be represented in a number of ways, including Euclidian distance, network distance, or some derivative of travel cost. In this case, Euclidian distance between points is computed as it constitutes the simplest approach and is computationally the least expensive. Agglomerative hierarchical clustering procedures are often represented graphically as a tree, or dendrogram: "cutting" the tree at different levels results in different levels of generalisation and cluster allocations. One observed inadequacy of the single-linkage method is the possibility of "chaining" in which individual observations are joined

because of proximity, but a chain forms as observations mutually joined through several links are actual very distant to each other.

Kenward et al (2001) describe their modified single linkage clustering method, which they primarily see as an adaptation that helps mitigate the effect of chaining and “fragmentation due to serial spatial correlation” (p. 1909), wherein the minimum cluster size is set as three locations. Kenward et al’s (2001 p. 1909) method follows this scheme:

- 1) First cluster formed of three locations based upon the minimum sum of nearest-neighbour distances.
- 2) This cluster gains a fourth location if the distance to its nearest outlier is less than the mean nearest-neighbour distance in the next potential cluster.
- 3) “After more than one cluster has formed, clusters fuse if the outlier being assigned to one is already part of another... If more than one cluster has the same distance to its nearest outlier, the cluster gains the outlier with the minimum sum of distances to every location in the cluster (effectively, the distance to its centroid)” (p. 1910).
- 4) Stop when a given cumulative percentage of the point distribution has been incorporated into a cluster.

The distinct disadvantage of this method, not apparent in the KDE method, is how point locations that exactly overlay other points are handled. Patients living in the same household and using the same GP surgery will thus have a 0 distance to their nearest neighbour, and any households with 3 or more patients will automatically form a cluster. Most likely, many of these initial clusters will be incorporated into larger clusters during the process, however outlying households will still appear as clusters. This problem can be mitigated by using the ESRI ArcGIS “dissolve” function, which can be used to transform points that overlay others into a single point for each location with a count field that specifies how many patients are represented by any given point. This effectively creates a weighting field that can be used in the calculation of the cumulative percentage of the point distribution captured by a given set of clusters.

6.3.3.2 Enclosing the clusters using shape characteristics

Having performed the modified single linkage clustering, a set of points is returned and, if a point has been included in a cluster, an indication of the assigned cluster is given. This allows

for a distinction to be made between multinucleated service areas, since each cluster can be encapsulated independently by a boundary. In terms of defining boundaries, Kenward et al (2001) suggest the use of convex hulls (minimum convex polygons), however there are alternatives that could be utilised, for instance a geometric median for each cluster could be defined, and Huff and Batsell's (1977) method then used for each cluster. Similarly, methods that aim to derive the "shape" of a point pattern can be employed: the shape is different from the hull as the shape will not necessarily be convex. Two methods for defining shape are considered – alpha shapes (α -shape) and chi shapes (χ -shape): either of these offer the opportunity to create a depiction of the shape of a service area.

The alpha-shape, or alpha-hull, is a generalisation of the "convex hull of a finite set of points in the plane" (Edelsbrunner et al, 1983). Fisher (2000) describes the method for constructing an alpha shape as:

"Imagine a huge mass of ice-cream making up the space \mathbf{R}^d and containing the points \mathbf{S} as hard chocolate pieces. Using one of these sphere-formed ice-cream spoons we carve out all parts of the ice-cream block we can reach without bumping into chocolate pieces, thereby even carving out holes in the inside." (p. 1)

In this context, "Alpha" is the radius of the "ice-cream spoon". The process can be graphically represented as in Figure 6.4.

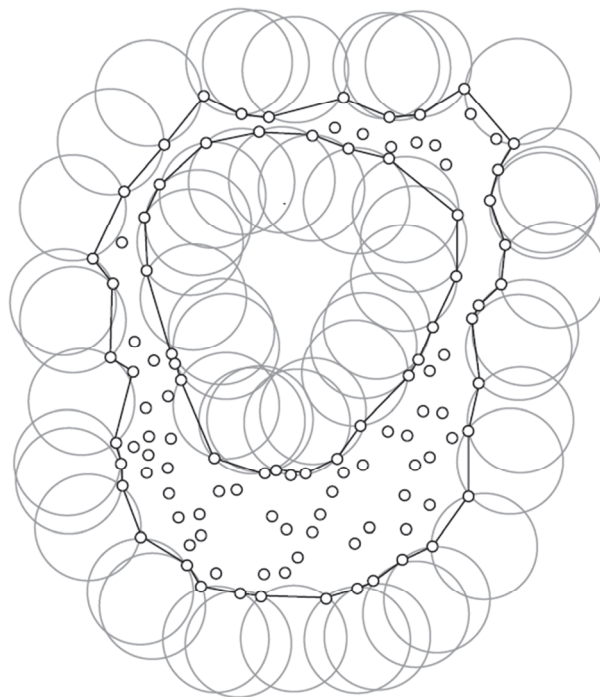


Figure 6.4: Demonstration of the creation of an alpha-shape for a set of 2D points
(source: Fisher, 2000 p. 2)

The chi-shape (Duckham et al, 2008) is a method of defining the shape of a set of points based upon the Delaunay Triangulation of that set of points. The Delaunay Triangulation is the dual of the Voronoi diagram discussed in the previous chapter, it links all points in the plane in such a way that the lines bisect every edge of the Voronoi diagram. The chi-shape is created by removing boundary edges from the Delaunay triangulation incrementally from longest to shortest, subject to a minimum length parameter that dictates the cut-off length for not removing edges, and that a removed edge will still leave a simple polygon behind. A simple polygon in this case implies that the resultant set of edges is still a triangulation and that there are not orphaned vertices (a vertex connected to only 1 edge). Figure 6.5 shows a number of chi-shapes dependent on the minimum length of edge that is allowed to be removed from the Delaunay Triangulation.

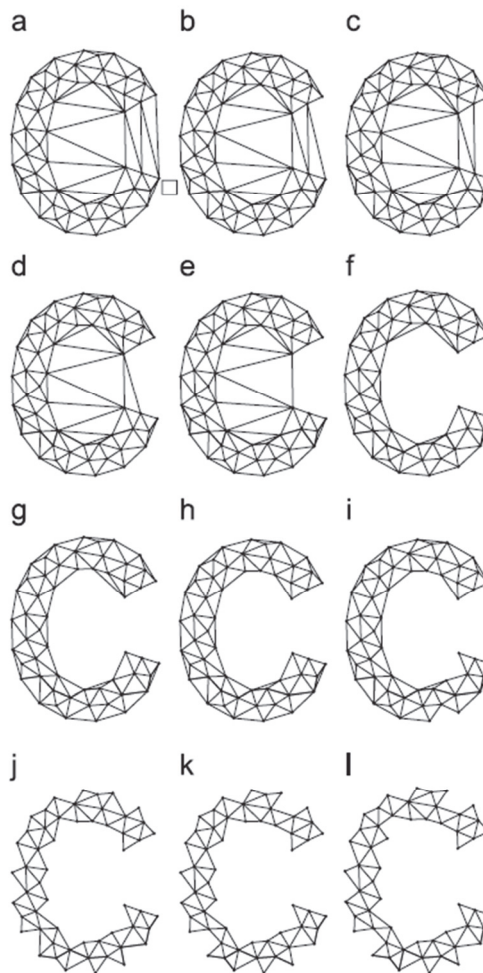


Figure 6.5: Chi-Shape results for different minimum length edge removal options (a = longest, l = shortest) from Duckham et al, 2008 p. 3230

For the size of point sets for which boundaries are being computed, either shape delineation option offers a good execution time, whilst both suffer from requiring an explicit

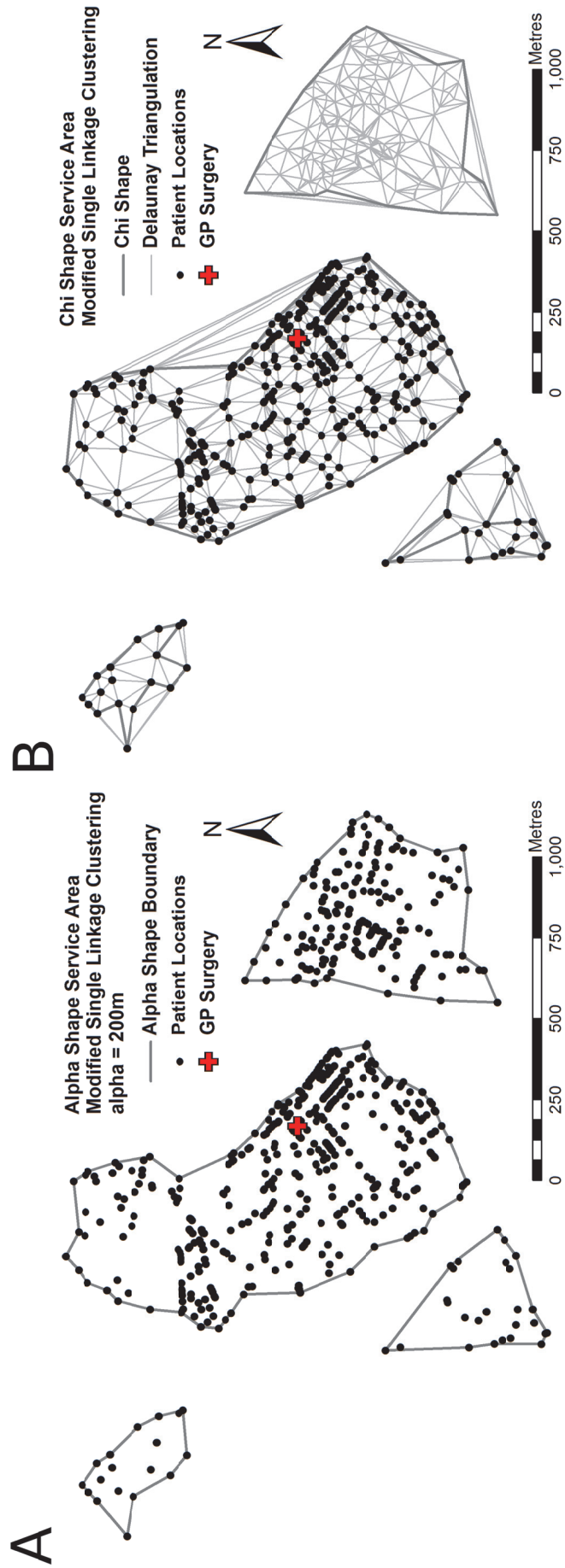


Figure 6.6: Service area for modified single linkage clustering approach defined by A) Alpha Shape and B) Chi Shape

parameterisation, either the radius of the circles in the alpha-shape, or the length of the minimum length edge to be removed in the chi-shape. The alpha-shape may offer an advantage if it is important to find holes within the point pattern, which may be the case. Figure 6.6 demonstrates the application of the modified single linkage clustering approach covering 75% of the patient distribution for the same GP surgery as in Figure 6.3, with A using alpha-shape delineation and B using chi-shape delineation. As is evident, the differences between the representations are negligible and largely subject to parameterisation, thus adoption of either is largely arbitrary and may come down to the ease of implementation. Figure 6.6 B demonstrates the chi shape as well as the full Delaunay triangulation: this demonstrates the extent of the minimum convex polygon (convex hull), clarifying the advantage to service area delineation that using a shape-based method can make.

6.3.4 A Minimum Convex Polygon Approach to Delineating Service Areas

The final method of interest to delineating service areas is based upon convex hulls, or minimum convex polygons. The convex hull of a point set is the smallest polygon that encloses a set of points in the plane without any concave edges, in practice it is the shape that an elastic band would take when put around a set of pegs, or dowels, fixed to represent a set of points. However, unlike the traditional approach to defining service areas which treat the convex hull as a process to be enacted on the data as a whole, or a predefined subset of the data which represents a set proportion of the point distribution, this method creates many smaller convex hulls and then creates a union of them in order to create a service area. In a sense this is also using the same nearest-neighbour type characteristics investigated in the previous section using cluster linkage methods.

6.3.4.1 k-Nearest-Neighbour Convex Hulls

Getz and Wilmers (2004) describe their method as a k-Nearest-Neighbour Convex Hull (k-NNCH) approach. Quite simply it involves drawing the set of convex hulls for a point pattern so that each point has a convex hull incorporating it and its (k-1) nearest neighbours. The complete union of all these convex hulls is therefore the “covering” from which “subcoverings” can be obtained which encapsulate a given percentage of the point pattern. The subcovering is calculated by incrementally creating a union of the smallest convex hulls

until such point as the desired percentage of points is included. The union of convex hulls forming the subcovering thus represents the isopleth of the densest set of points.

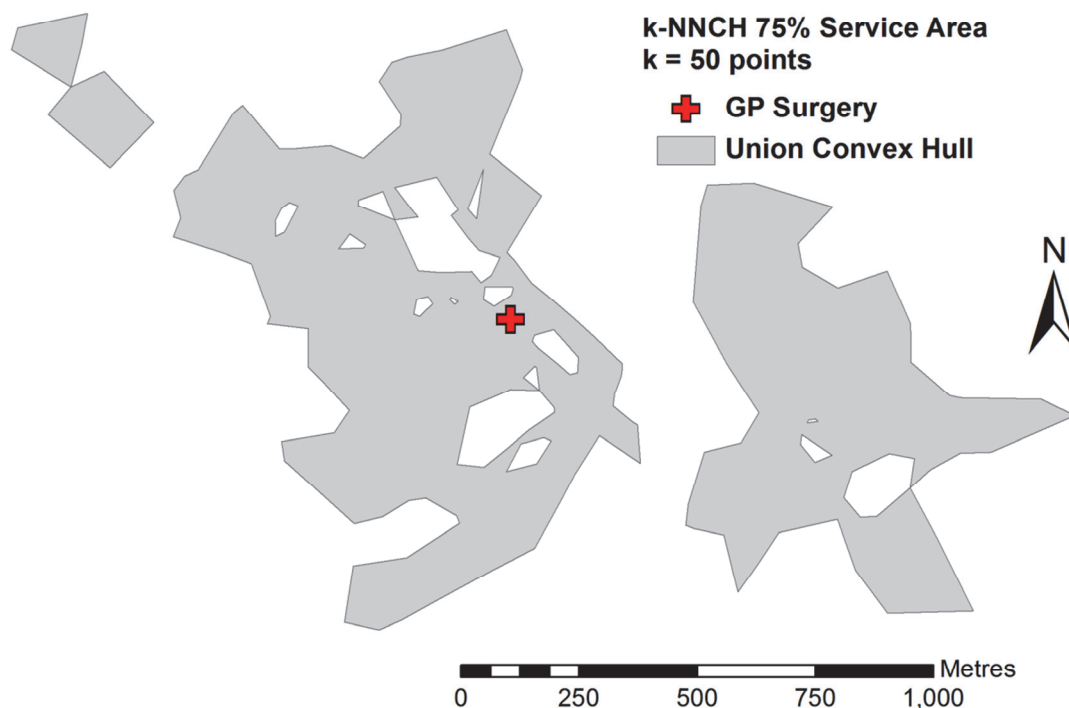


Figure 6.7: k-NNCH service area covering 75% of a Southwark GP surgery's patient distribution, with $k = 50$.

The key consideration to the k-NNCH method is setting an appropriate value for k . Getz and Wilmers (2004) attempt to provide a solution for this, which they describe as the "minimum spurious hole covering" (MSHC) rule. Application of the MSHC rule involves selecting the "smallest value of k that produces a covering that has the same topology as the given set" (p. 491). However this requires two things: firstly, a knowledge of the expected topology, which Getz and Wilmers (2004) acknowledge; and secondly, a dedication to iterating through all appropriate values of k in order to subjectively select the best one. When the topology of the service area to be created is unknown, or uncertain (as may be the case in the context of GP Surgery registration due to patient behaviours, and/or GP surgery constraints), it is difficult to subjectively assess what is a "spurious" hole as opposed to a "real" hole. Setting k for uncertain topologies again seems to come down to iterative working, and experience, which places a burden on the researcher. As with the cluster linkage method, the k-NNCH method also suffers as a result of points that overlay each other. Figure 6.7 demonstrates a service area for a Southwark GP surgery using this method.

6.3.5 Service Area Delineation: Consolidation

Having considered the use of service areas in Geography, and identified the continued development of methods of delineating a point pattern available in Ecology, three prominent methods were considered for use in health services research. Whilst Lewis (2010) has considered the effectiveness of some service area models for use in health, and found, like Getz and Wilmers (2004), that kernel-based methods are less effective than the others tested, kernel-based methods are much more desirable in practice than the others for several important reasons:

1. Kernel methods require considerably less computational time than the other methods, particularly the cluster-linkage method which suffers substantially as the number of data points increases.
2. Kernel methods are easier to implement in a GIS, where density analyses are commonplace and well understood. The convex-hull method requires a substantial amount of scripting to implement, and the cluster-linkage method requires bespoke programming.
3. The PVC output of the kernel method is suitable for visualisation, as the spreading effect of the kernel essentially anonymises the locations of patients in the underlying point pattern; in either of the other two methods, vertices represent the actual residential location of a patient which may constitute a breach of data security if it were possible to derive coordinates for those points (i.e. from a grid, or addition of local context).
4. The location of patients are geocoded to an arbitrary point representing the centroid of a building; however these are subject to uncertainty. For instance, a large social housing estate may be geocoded to a single point representing its "centroid" when in reality its extent is wider, the fuzzier aspect of the kernel approach may actually be more representative of the situation on the ground. Longley et al (2005), in discussing Thurstain-Goodwin and Unwin's (2000) study of town centres suggest that in research where the need to communicate with decision makers is paramount, precision is not absolute.
5. The kernel methods, used in the way described, can be automated to batch process large datasets. Whilst this is possible for the other methods, the parameterisation of certain aspects of the methods would require human interaction, arbitrary pre-

selection, or the engineering of sophisticated solutions beyond the scope of this thesis.

The next section constitutes an analysis of service areas for Southwark GP surgeries using the kernel method detailed previously.

6.4 Assessing Patient Registration Patterns with GP Surgeries in Southwark: A Service Area Approach

6.4.1 The Approach

The approach of this section is to use service areas, derived for individual GP surgeries, in order to assess variations in registration patterns. The method is similar in nature to Harris and Johnston's (2007) paper on assessing polarisation in primary schools; however, this thesis uses a different method for delineating service areas, and applies it more consistently across each surgery, and seeks to derive alternative insights into behaviour.

The general approach is two-fold. First, the question of "what is an appropriate percentage of the distribution that ought to be delineated as a service area?" is considered.

Subsequently, an index-based approach is introduced which indicates whether the patients of a particular GP surgery within a service area are representative of the service area population as a whole. Findings in this respect are discussed in the context of providing service to a "community", and the differing needs and requirements that this might entail.

6.4.2 Percentage Delineations of Service Areas

It is unclear what percentage of a patient distribution ought to be enclosed by a service area for the purposes of healthcare services research, as discussed 60-70% is often touted as a useful delineation in market area analysis, whereas in Ecology, the delineation of a home range is often done at the 95% or 99% interval (Schoener, 1981). The reasoning behind these figures more often stems from experience rather than empirical evidence, however in the ecological literature Ford and Krumme (1979) suggest that large steps in the area of home ranges as the percentage delineated increases might indicate useful breaks that allow a core home range to be defined exclusive of outlying patients. This is useful because including the residential locations of patients who live substantially further away from a GP surgery than the majority of patients may also require the inclusion of areas of space within which no users of a particular service come from, such a situation is thus hardly

representative of the core service area of a particular surgery. However, as levels of registration with a GP surgery decays with distance by way of a power, or exponential, distribution (as demonstrated in Chapter 3), we could expect that the area of the associated service area would increase in much the same manner. Figure 6.8 demonstrates that this is in fact the case.

Figure 6.8 demonstrates that initially the area of a service area increases very slowly, as patients tend to register with geographically proximate services, however as greater and greater percentages of the patient distribution are incorporated into the delineated area, the geographical space that is bounded increases roughly exponentially, such is the effect of outlying patient registrations. However, this is not wholly consistent across all GP surgeries, if a line drawn on the diagonal of the graph is taken to be a situation of equality, in which increase in the area of a service area is proportional to a corresponding increasing in the percentile of patients delineated, then it can be seen that some GP surgeries are closer to this line than others. Naturally, the situation of perfect equality would be essentially unachievable in an urban environment due to the effects of spatial structure, such as the presence of parks and open spaces, or high density housing developments. Further, the equality line suggests that the effect of location on registration is consistent within the largest defined service area, that the registered population would be evenly distributed, rather than more concentrated closest to the service location. Figure 6.8 suggests that the spatial characteristics of some GP surgeries are rather different to others: the “most equal GP surgery” for instance has a distribution of service area sizes that are more evenly spread across the percentiles of its service area. Conversely, the “least equal GP surgery” tends to have smaller areas representing the majority of its service area percentiles. There are several reasons why this could be the case: the “least equal GP surgery” could be located in an immediate area of particularly high density population, or be subject to more patients travelling unexpectedly long distances than other GP surgeries. Similarly, the “most equal GP surgery” could be in a lower density area, with less competition for patients from other GP surgeries. In fact, all of these observations are true, however they do not give any specific guidance as to what an appropriate percentile break would be to best represent service areas for the set of Southwark GP surgeries.

As has been stated, there is a distance decay effect in the pattern of patient registrations with GP surgeries, and Figure 6.8 exhibits a roughly exponential decay in the distribution of

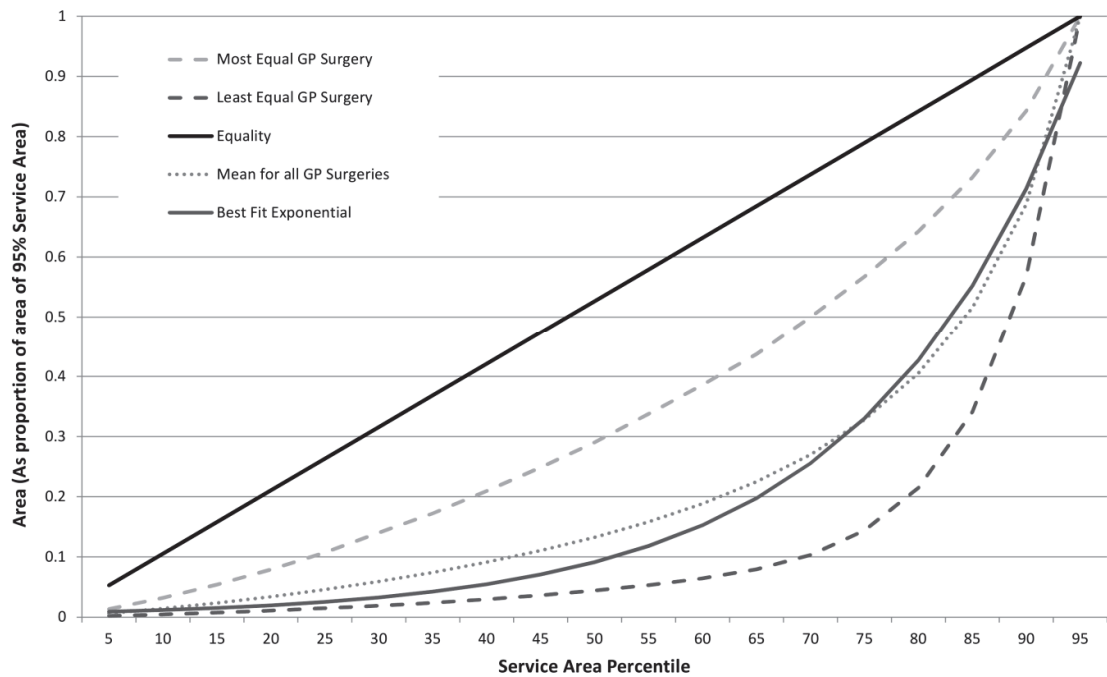


Figure 6.8: Graph of Area of delineated Service Areas (relative to size of 95% service area) against service area percentile.

the area of service area percentiles. However, given that the exponential curve is smooth, there is little to suggest a relevant value at which to cut the curve and assert that the given percentile at which the cut was made represents an effective core service area. In order to answer this question, the focus is instead placed on the patients within the service area. When a service area is very small, it would be expected that the highest proportion of patients within that service area would be those using the GP surgery for which the service area was defined, this is evident in Chapter 5, Figure 5.6. However, as the service area increases in size, there is an increasing chance that newly included patients will not use the GP surgery whose service area they find themselves within. Therefore, the proportion of patients in a large service area, using the GP surgery for which that service area is defined, may not be greatly different to that of patients using other nearby GP surgeries. In order to calculate a useful percentile cut-off point for GP surgery service areas in Southwark we look for the point at which a GP surgery service area has become so large as to make the proportion of patients using that surgery insignificant in light of the proportion of patient also within the service area using other GP surgeries. When the service area fails to capture a concentration of patients belonging to its GP surgery, then it can no longer be considered a representative, or a “core” service area.

In order to find the appropriate service area percentile, for each GP surgery, for each percentile computed (5% - 95% in steps of 5%), the proportion of patients registered with each GP surgery present within the service area is computed subject to the total number of patients within the service area. The inter quartile range (IQR) of these proportions is then computed, and a datum of 1.5 times the IQR above the upper quartile is taken, if the proportion of patients using the GP surgery of the service area is being tested is higher than this datum, then we move onto the next percentile. This testing is continued until such a point as all percentiles are exhausted, or the proportion of patients in a GP surgery falls below the datum, indicating that other GP surgeries have similar proportions of registered patients within that service area. Two different measures of proportions are used, firstly, the simple proportion of patients in a service area using a given GP surgery, and secondly, that same proportion normalised by the GP surgery's list size subject to the whole population of Southwark. The second measure adjusts for the relative sizes of GP surgeries, allowing smaller surgeries to be measured alongside their larger counterparts. Table 6.1 shows the counts of GP surgeries which reached an effective cut-off point at each service area percentile interval.

	40	45	50	55	60	65	70	75	80	85	90	95
Prop.	0	0	3	2	1	0	2	4	2	3	3	26
Norm. Prop	2	3	1	1	1	4	1	2	5	5	5	15

Table 6.1: Counts of Southwark GP surgeries that are concentrated in Increasing percentage service areas

In Table 6.1, over half of the 47 GP surgeries in Southwark can be represented by the 95% service area. The GP surgeries that fall below this are in general the smaller surgeries, or average sized surgeries in areas of clustered service provision. However, when accounting for surgery size, more of a balance is obtained as the absolute effect of surgery size is mitigated, and now only a third of GP surgeries can be represented by their 95% service area. The spread of core service areas is large, as was anticipated by Figure 6.8, fewer GP surgeries are best represented by lower percentile value service areas, but in terms of having a consistent and comparable approach to service areas across the whole of Southwark, the weighted average of the normalised proportion results is taken, which is 80% (to the nearest computed service area interval, the actual result is 79.11%). A depiction of all the 80% service areas for Southwark GP surgeries is shown in Figure 6.9, which demonstrates the complexity of registration with GP surgeries in Southwark, a 3-colour ramp is used to aid with the distinction of services areas over the large range of classes evident. Figure 6.9

reveals the same central areas as having multiple overlapping service areas as are present in Figure 6.1.

In the Chapter 7, the 80% service area interval is used to describe the set of different GP surgeries with which a patient could potentially register. However, in the next section of this chapter, the full range of service area intervals are used to detect patient behaviours with regard to GP surgery registration.

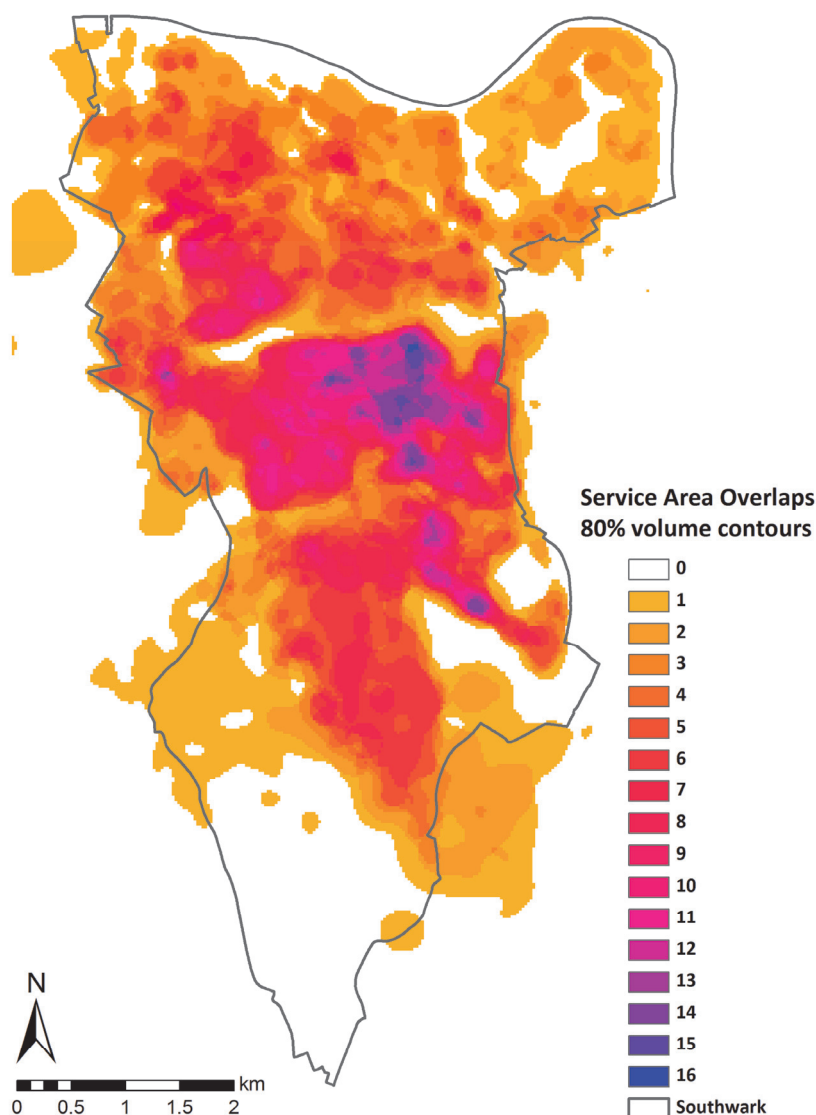


Figure 6.9: Overlapping service areas in Southwark for 80% volume contours

6.4.3 Detecting Patient Registration Behaviour with Service Areas

Patient behaviour with respect to registration with a particular GP surgery can be understood in terms of patterns of registration evident at the GP surgery level. When patients with distinct characteristics, be it their sex, age or ethnicity, concentrate their

registration with a particular GP surgery relative to what might be expected given the local population composition, we assume that there might be a reason for this. Better understanding why particular population groups chose particular GP surgeries can help policy makers and planners understand the local context for healthcare, and provide more effective services.

Service areas are used as a filter, effectively delineating the *de facto* community that a GP surgery serves. This measure of community is intuitive as it is derived from the actual pattern of patient registrations with GP surgeries, and it supports the complex nature of interactions evident in an urban environment in which service provision is dense, highly accessible and subject to overlaps in terms of the communities served.

Using each of the previously defined service area intervals, from 5% to 95%, for each of the GP surgeries, the differences between patients registered to a given GP surgery compared to the total population of that GP surgery's service area are considered. By exploring the possibility of their being differences across the whole range of service area percentiles for each GP surgery, a behavioural transect is effectively created, this allows for variations in patient registration behaviours to be considered. In a sense, each set of service areas can be treated as a profile of the behaviour of patients in accessing each GP surgery, with the profile defined by the desire to investigate a known demographic attribute of the patients themselves. Within each service area, the following index can be defined:

$$Index = \frac{\text{Proportion of Patients of [particular attribute] using GP}}{\text{Proportion of Patients of [particular attribute]}} \quad (6.9)$$

In which a value of 1 suggests that the patients with a given attribute registered with a particular GP surgery are representative of the patients with that attribute in the service area as a whole. A value of < 1 indicates less usage than expected of that GP surgery by the group of a given attribute, and conversely, values > 1 indicate greater usage.

Interpreting the size of the index value, essentially the effect size, is a difficult matter. An index value of 2, would indicate that twice as many patients with a given attribute have registered with the GP surgery in question than would be expected given the composition of the service area as a whole. However, in practice it is difficult to suggest what difference that makes – is the statistically observed effect actually noticeable in practice and does it describe an actual behavioural aspect of patient registration? For instance, is the fact that twice as

many people of a given characteristic are using that GP surgery contingent on a characteristic of the service, or of the patients, and does it change how service is delivered in that surgery? This is fundamentally a subjective question, and pertains to the discussion of location quotients in chapter 4, how big does a location quotient have to be in order for it to represent a concentration of whatever is being investigated. It is possible that small index values in this chapter are not really observable in reality. Nevertheless in statistical terms, perhaps as a result of the fine scale of analysis and the large number of observations, they do seem to represent small observable trends in registration, but their value should be subject to a consideration of the context of the GP surgery in question.

6.4.4 Analysis of Indices for GP Surgeries in Southwark

The method detailed above works well with categorical data, in general continuous data, such as age will need to be grouped. With this in mind, the Southwark patient register was investigated to see whether patient sex, patient ethnicity, or whether patients lived in social housing, suggested different patterns of registration with GP surgeries.

6.4.4.1 Patient Sex

There have long been empirically demonstrated relationships between the patient and the choice of GP by sex (Joseph and Phillips, 1984), with trends showing that male patients prefer male GPs and vice versa. However, as this analysis is conducted at the GP surgery level, with service units consisting of many GPs, there is almost no pattern to be found that suggests a preferential registration of patients by sex with any particular GP. The two GP surgeries that deviate from the rest, apparently demonstrating a relationship between patient sex and a particular GP surgery, are shown in Figure 6.10.

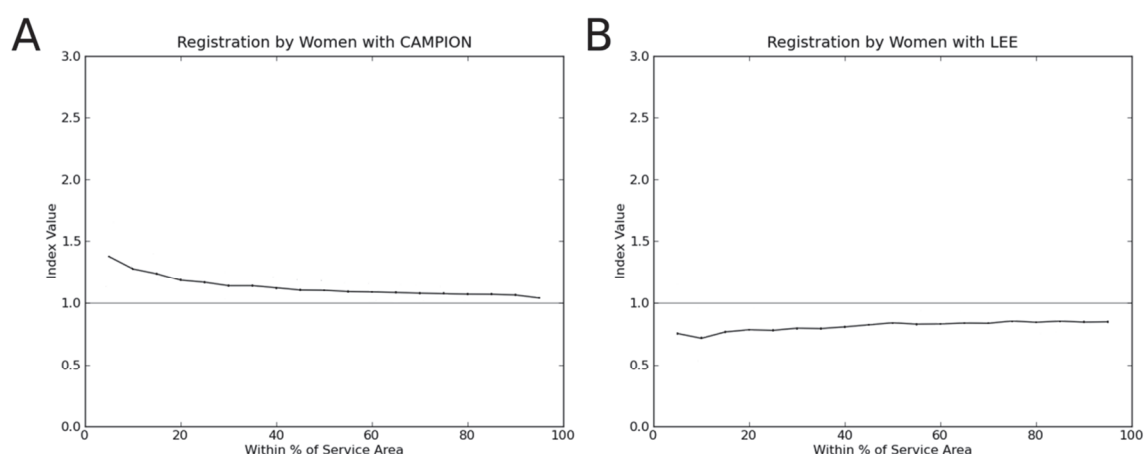


Figure 6.10: Two GP surgery profiles in which patient sex seems to indicate choice-like behaviour.

The actual values of the indices are small, however both tend to suggest a consistent over (6.10 A) or under (6.10 B) representation of female patients in the surgeries concerned (GP Campion's surgery, and GP Lee's surgery). It is certainly true that the surgery in A employs 2 female doctors, and 1 male and that may offer some explanation, however, the behaviour in B is likely to be better explained by ethnic factors shown in section 6.4.4.3. It may be the case that marked differences occur at the level of the GP, rather than the surgery as demonstrated here, however the recent requirement that a patient be registered with a GP surgery, rather than a specific GP, may have diluted this effect somewhat. Whilst undoubtedly some patients would prefer to see a GP of a particular sex, this is not evident in registration data for Southwark.

6.4.4.2 Patient Tenure Type (Social Housing, or Other)

Social housing is a spatially fixed phenomenon; as has been noted previously, Southwark has a very large stock of social housing, and the pattern of GP surgeries seems to reflect this to some extent (Chapter 3). However, like the sex of the patient, there seems little to suggest that whether a patient lives in social housing can affect their likely GP surgery of registration. Six GP surgeries show some evidence that they serve a lesser proportion of patients than might be expected given the composition of their service areas, this trend is not mirrored by other GP surgeries serving more patients living in social housing however.

The four surgeries showing the strongest trends are shown in Figure 6.11. Only D demonstrates a situation in which the index falls below half of what might be expected. Thinking back to Chapter 3, it was suggested that living in social housing might have an effect on the potential to access a GP surgery given the high population density in area associated with social housing. Two of the profiles (B and D) in Figure 6.11 show that the immediate service area of GP surgeries are unlikely to be particularly different from what could be expected given the patient composition of the service area. However as the service area grows to incorporate a greater percentage of the patient distribution, the proportion of people living in social housing using those GPs declines relative to the proportion in the service area. There is little to choose between those patients that live in social housing as opposed to those that do not in distance terms, their respective average distances to either their nearest GP, or the actual GP used, are almost identical.

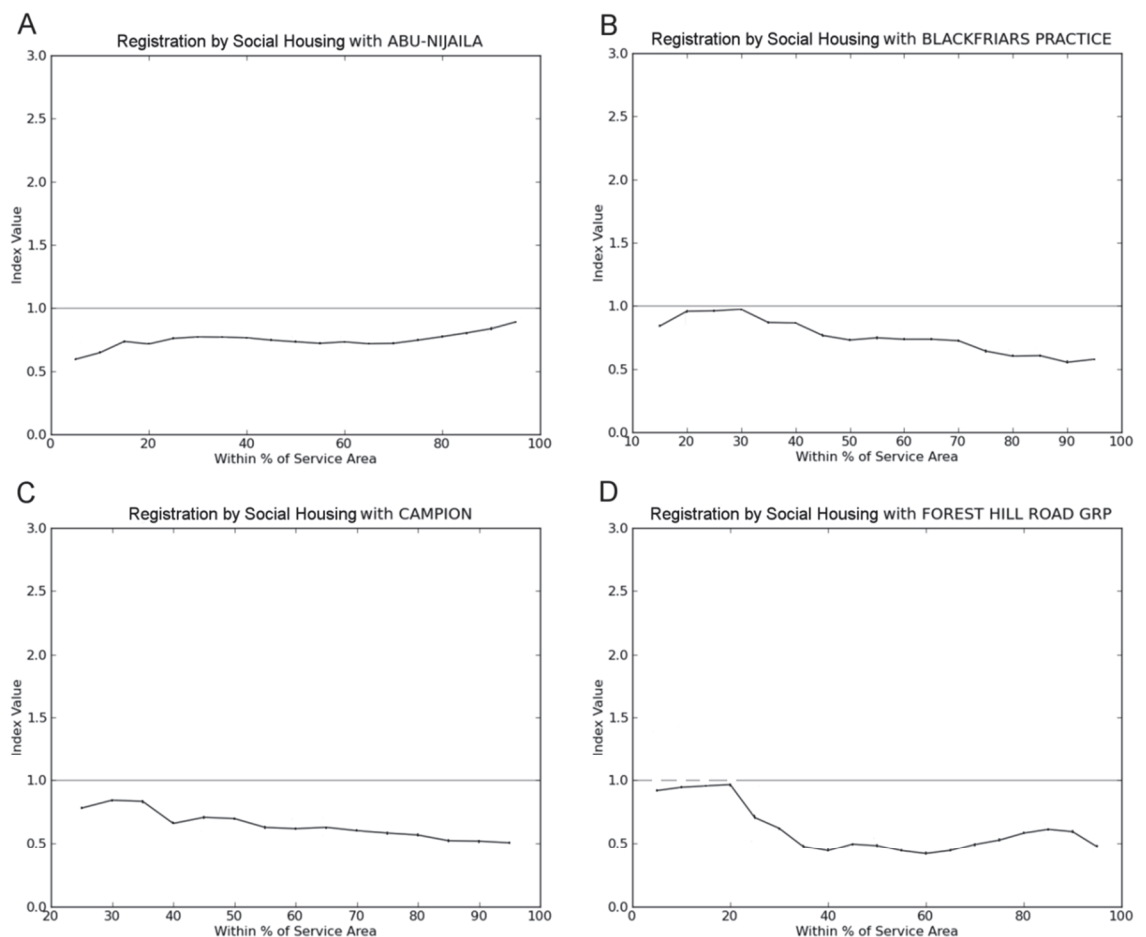


Figure 6.11: Four GP surgeries in Southwark that demonstrate a lesser provision of service to patient living in social housing than might be expected given their service area composition in terms of housing stock.

Whilst GP surgeries are incentivised to treat patients from deprived areas, as a result of concerns surrounding differentials in access to care, there is comparatively little in Southwark to suggest any kind of systematic preference or constraint affecting patients living in social housing compared to those that do not.

6.4.4.3 Patient Ethnicity

Few areas in the UK are as multicultural as Southwark, and indeed few are subject to the level of population change and immigration that Southwark is. This provides a provision and management challenge to Southwark's GP surgeries. When the physical, and web, presences of the Southwark GPs are considered, language is a key point of reference in provision of care, around half of the GP surgeries (24 of 47) make specific reference to the languages spoken on either NHS choices, or their personal websites. In fact, one GP surgery even details how an interpreter can be acquired for patients with language requirements. Plates 6.1 and 6.2 demonstrate that some GP surgeries even publicise the languages catered for on their surgery facades. Further, analysis of the Onomap origins of the GPs associated with

each GP surgery in Southwark reveals a heterogeneous mix of ethnic, cultural or linguistic origins (see Chapter 5, section 5.3.5).



Plate 6.1: Sign outside the Dun Cow Surgery, Southwark, announcing languages that their GPs can consult in.



Plate 6.2: Sign for Dr Lee's Surgery, with simplified Chinese characters, and Spanish speaking announcement (Castilian Spanish differentiates from Latin American, and North African, Spanish dialects).

Analysing the possibility for patient ethnicity playing a role in the pattern of registration with a GP surgery demonstrates some interesting patterns, although there are 24 GP surgeries (c.

50%) that show no signs of having a patient ethnic composition that is anything other than what could be expected given the patient population present in their service areas. In general, the differences in local compositions are most notable amongst minority ethnic groups, particularly the African, Muslim and East Asian groups. Figure 6.12 shows the 8 highest index scores for particular ethnic groups in Southwark GP surgeries, the remaining 10 ethnic groups for which there is some evidence of increased registration with a GP surgery compared to the ethnic composition of the service area fall below an index value of 1.5, there are no GP surgeries that have high index values for British patients, although 3 GP surgeries show values just above 1 (all less than 1.5), which given the size of the British group in Southwark may have practical significance.

The East Asian ethnic group gives rise to the two highest scores across all Southwark GP surgeries and ethnic groups, suggesting a real specialisation for care provision for that particular group, with East Asian patients up to six times more likely to use these GP surgeries than could be expected. However, whilst Fig 6.12 A is the GP surgery depicted in Plate 6.2, which in addition to a Chinese GP, clearly advertises its credentials as a GP surgery for East Asian patients; Figure 6.12 B actually relates to a GP surgery that operates as a primary care walk in centre. This may suggest a cultural difference in how primary care is accessed that is not being provided for in Southwark as widely as may be necessary – in China primary care health centres are only just now being introduced. It may also reflect a historical preference as the previous lead GP at the walk-in centre was a Dr. Maung – which Onomap contends is a Burmese name. In Figure 6.12, graphs C, D and G demonstrate GP surgeries who seem to over recruit Muslim patients from their service areas, interestingly, whilst C and D over-recruit very locally, in the earlier percentage delineations of their service areas, as well as more distantly in the higher percentages, G only seems to have the more distant effect. In all cases, C, D and G show a tendency to over-recruit disproportionately at the extremes of their service areas, this may be because in the extremes of the service area there is likely to be closer opportunities for patients to register with a GP surgery, thus any evidence of behaviour contrary to the tendency to use a near GP surgery is effectively magnified. The suggestion is therefore that Muslim patients either choose to, or by constraint have to, travel further to use these GP surgeries if nearer alternatives are not fitting, one commonality between surgeries C, D and G is the presence of Muslim and other

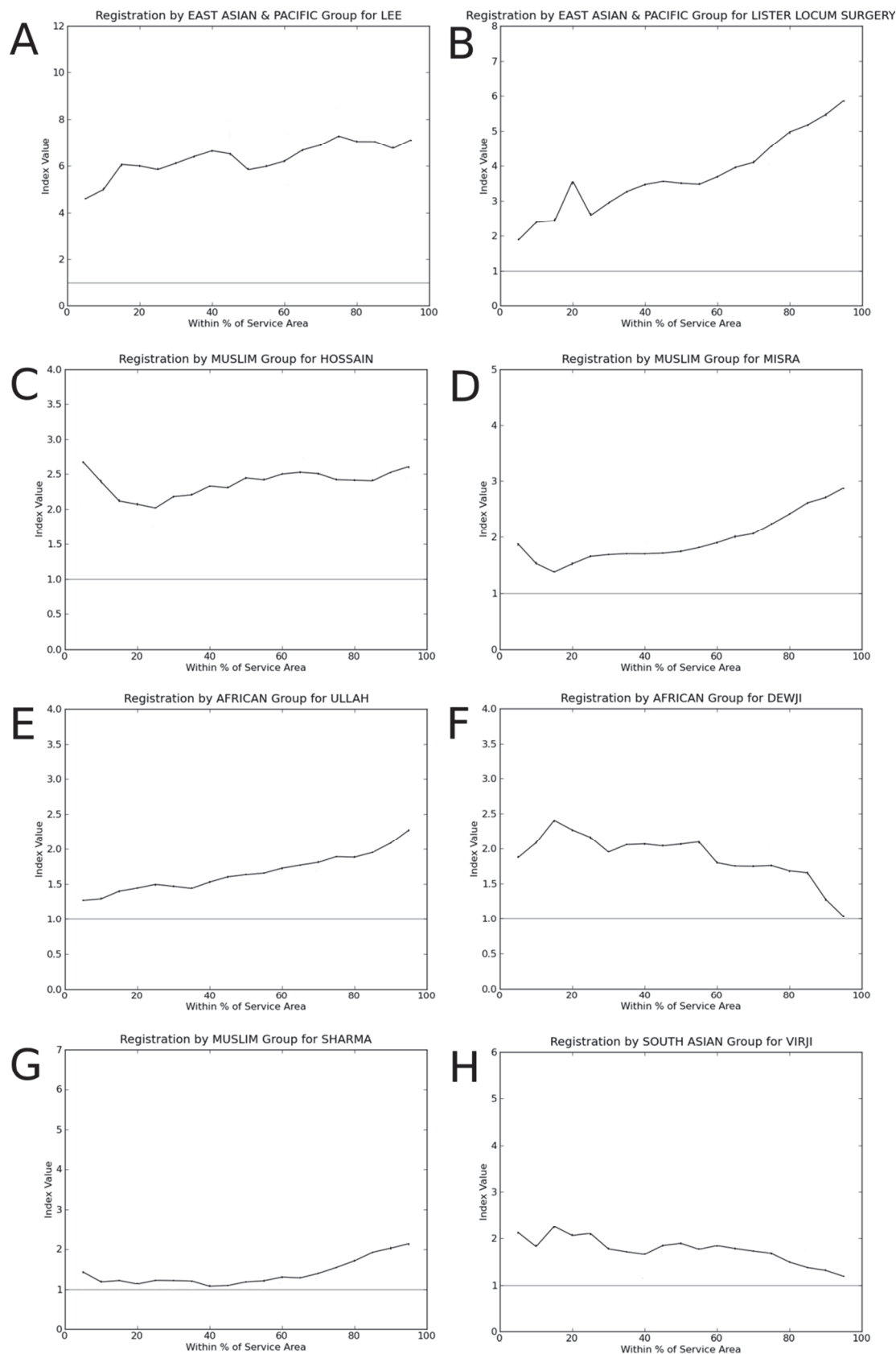


Figure 6.12: Local ethnic concentrations in GP surgeries based upon service area estimations, top 8.

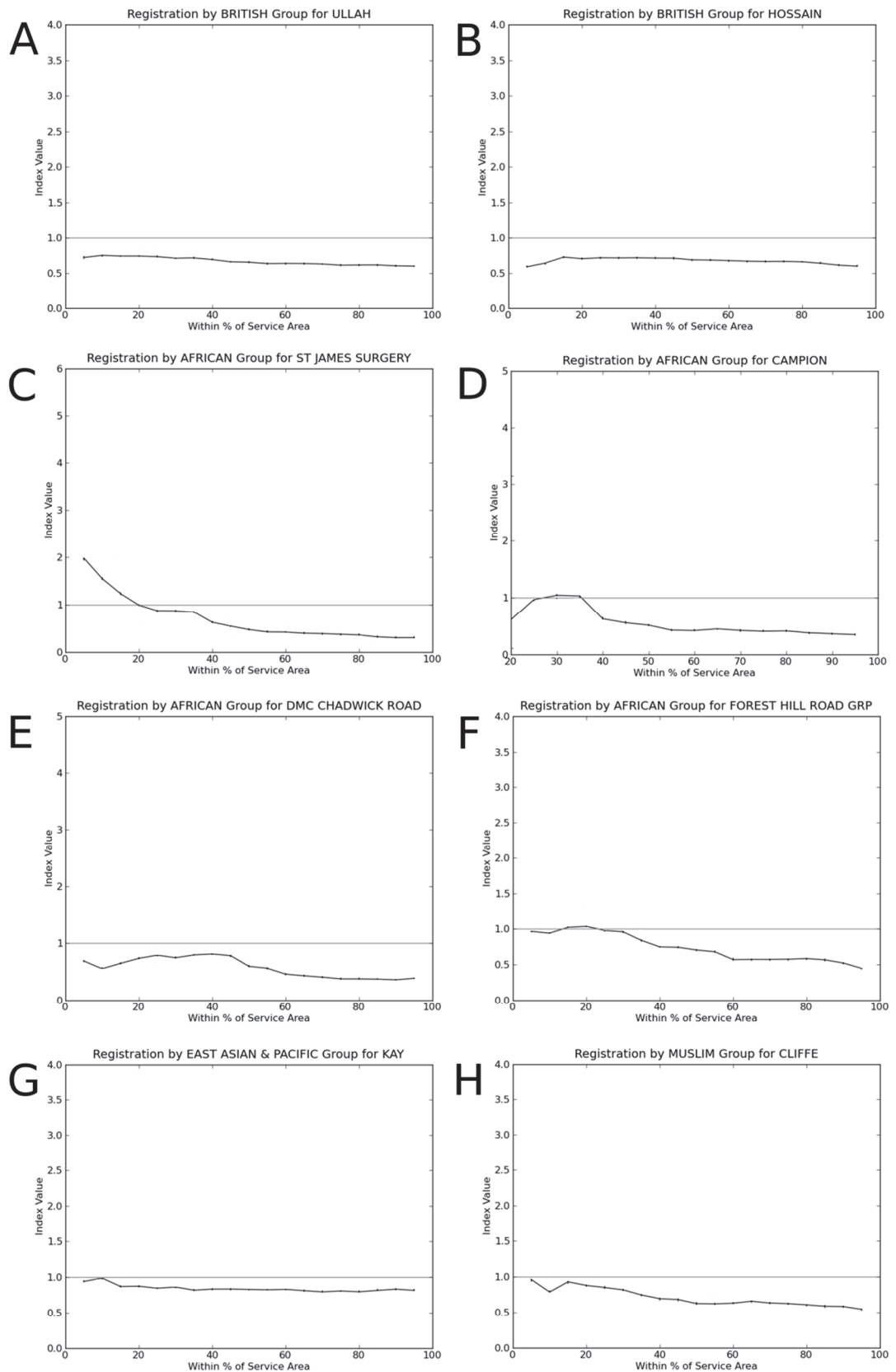


Figure 6.13: Local ethnic dispersal in GP surgeries based upon service area estimations, bottom 8.

ethnic minority GPs. Figure 6.12 E shows a similar trend for African patients, however Figure 6.12 F and H show a different pattern, in which African and South Asian patients respectively experience a concentration locally, which falls off to expected levels as the service area expands.

Figure 6.13 demonstrates the eight lowest index scores, indicating GP surgeries in which registration by particular ethnic groups is less than could be expected given the service area composition. In many cases, these represent the balancing of patient registration caused by concentration of patients in particular GP surgeries in Figure 6.12. The British ethnic group shown in Figure 6.13 A and B has lower levels of registration than might be expected with the given GP surgeries, perhaps as a result of the tendency for African and Muslim patients to concentrate in these GP surgeries, however it is unclear whether this is a simple balancing effect, or whether it constitutes an active choice on the part of patients. The sub-Figures D, F and H in 6.13 demonstrate lower than expected levels of registration for African and Muslim groups, which reflects the results for social housing in section 6.4.4.2, remembering that Chapter 4 shows that the African and Muslim population of Southwark are most likely to live in social housing. Figure 6.12 G shows a GP surgery that is proximate to the GP surgery shown in Figure 6.12 A, which demonstrates a lesser proportion of East Asian patients than expected, likely based upon their tendency to go to the GP surgery in Fig 6.12 A.

Table 6.2 gives an overview of the incidences for all ethnic groups in which the pattern of patient registration demonstrates either concentration or dispersal with respect to the service area of the 23 GP surgeries for which patterns are significant. Numbers add up to more than 23 because most GP surgeries demonstrate these patterns for more than 1 ethnic group, the patterns by ethnic group that were not illustrated in Figures 6.12 and 13 all have a maximum or minimum index value between 0.8 and 1.5, which are significant, albeit smaller values which might lead to questions regarding the practical impact of such observation – they do nevertheless reveal some smaller behavioural trends, and there is no quantitative reason to ignore them.

Index	African	British	E. Asian	E. Euro	Euro	Hispanic	Muslim	S. Asian	Unclass
High	5	3	5	1	1	3	6	2	2
Low	11	5	5	1	3	1	5	1	1

Table 6.2: Number of GP surgeries, by ethnic group, showing some evidence of concentration (high) or dispersal (low) of patients within service areas.

The overview presented in Table 6.2 suggests that there is at least some preferential behaviour for particular GP surgeries being exhibited by all ethnic groups. This can be interpreted as a higher concentration (or a dispersal) of a particular ethnic group registered with a GP surgery than could be expected given the patient composition of the service area itself. For the most part these effects are relatively small, although larger effects are indicated in Figures 6.12 and 13. Of particular interest is the fact that the concentration or dispersal of most ethnic groups is broadly speaking balanced, however the African group seems to concentrate in fewer GP surgeries than it is dispersed from. This may reflect cultural practice and social network effects that reinforce the use of particular GP surgeries, or might equally reflect constraints, such as the effect of high population density discussed in Chapter 3 when considering “potential” to access a GP.

6.4.5 Service Area Profiles for Southwark

In most cases there is clear evidence that GP surgeries in Southwark serve the set of patients that they would be expected to serve given the composition of their service areas. Equally, there is evidence for some GP surgeries having a concentration of patient registrations from particular ethnic groups, which suggests some preferential or constraint-based behaviour on the part of the patients. Of course, these patterns give little indication of the consequences for efficiency, or equity, of service provision, although it might be assumed that some of these patterns relate to patients exercising the kind of choice that recent NHS white papers have sought to develop. Naturally, densely populated urban areas such as Southwark are likely to be the sort of sites where patient choice can best be exercised, with the potential for real equity improvements if patient needs are met by the most suitable GP surgery, rather than simply the closest. Having said this, there is clearly a balance to be struck between effectively serving a local community, and leveraging aspects of the GP surgeries themselves to provide more directed care to particular groups. This is the choice between a consistent standard which all services adhere to, versus individual GP surgeries, or more likely, consortia of GP surgeries forging distinct paths based upon the preferences of their local patient populations. It is unclear what the effect of such a change in healthcare service provision would entail for the spatial equity of the system as a whole, however, an improved articulation and understanding of what a community is, perhaps in line with the articulation of a service area given in this chapter, could help generate a fuller understanding of how GP surgeries actually interact with local communities, beyond the rhetoric of policy documents.

6.5 Consolidation

This chapter has demonstrated a method for profiling registration with GP surgeries by deriving their service area from the distribution of registered patients. It considers the background regarding the development of market area analysis in Spatial Science and Geography, and introduces and illustrates three methods of delineating home ranges from Ecology. A method involving kernel density estimation (KDE) and the creation of percent volume contours is selected in preference to two other on a practical basis, and implemented in the profiling of Southwark GP surgeries. Using service areas of incremental percentage coverage, profiles are constructed for each GP surgery in Southwark based upon the patient's sex, whether they live in social housing, and their ethnicity as defined by Onomap. This analysis shows distinct patterns in patient registration with Southwark GPs for around half of all surgeries, suggesting local behaviours of concentration or dispersal, in some cases it is speculated that these patterns relate to a preference on the part of the patient to use see a GP of the same or similar ethnicity, whilst in others it is possible that constraints in the provision of service are introducing some patterns. Most notable amongst the ethnic groups for demonstrating evidence of choice-like behaviour are the African, Muslim, and East Asian groups.

In the next chapter, elements of this, and the previous chapter are brought together in order to model how patients with varying socio-demographic characteristics differentially access primary care GP surgeries in Southwark.

7. Patient Primary Care Registration Behaviour in Southwark

7.1 Introduction

In the previous two chapters, spatial models have been employed to offer insight into compositional differences in the demographic characteristics of patients served by Southwark GP surgeries. In Chapter 5, a normative model was used to create non-overlapping “market areas”, subject to the capacity constraints of the GP surgeries. This produces a representation of service by GP surgeries consistent with NHS primary care principles: that a patient should use their nearest GP surgery. However, in practice, and in particular in a service dense, population dense, inner city environment such as Southwark, it does not accurately represent the actual geographical assignment of patients by GP surgery. This is evident in the empirical differences between the observed and a normatively generated patient register: the majority of patients are not registered with their nearest GP surgery.

In Chapter 6, the idea of market areas was expanded, using “service areas” which helps us move beyond the normative geometry of the Christaller, to something much more akin to the actual spatial pattern of registration of patients in Southwark. Further, a service area can be defined uniquely for each GP surgery, without the need to aggregate the patient lists of GP surgeries which collocate, using the same premises. Further, rather than deriving a market area with regards to normative criteria, such as the minimisation of trip distances to a centre, the service area takes its definition from the observed point pattern of patient registrations – it thus makes no premeditated assumptions about the value of distance or time travel to a centre, seeking only to describe the boundary of interactions with a GP surgery. Naturally, whereas the market area creates an exhaustive representation, leaving no holes, and creating crisp edges to each market area which abut one another; service areas manifest the outcome of behaviour of the patients themselves, and the desire to delineate a “core” service area means that the service area of any given GP surgery will likely overlap with others, whilst leaving some patients within Southwark underserved. In order for a service area to include a set of patients within it, there has to be a given number of patients

locally actually using the GP surgery for whom that service area has been defined, therefore, overlaps highlight areas in which patients are likely to have multiple options with regard to accessing care. The density of service provision, and evidence of choice on the part of patients means that there are numerous overlaps and congruent service areas in Southwark: patients are not beholden, in a sense, to their nearest GP surgery.

In the previous two chapters, the inadequacy of a normative approach to understanding GP composition was demonstrated, whilst the service area approach demonstrated that a large number of GP surgeries in Southwark exhibit different patient compositions given the structure of their local “community” as estimated through their service areas. However, the insights in these chapters are univariate: they do not draw on the possibility of different ages structures in different ethnicities, or variation by age and sex, for instance. Further, whilst the importance of the GP surgery has been discussed in both chapters, with a classification of GP surgeries in Chapter 5 demonstrating different registration behaviours, and trends in registration by patient characteristics being broadly linked to the composition of different GP surgeries. However, in Chapter 6; there has been little to definitively link the importance of patient characteristics with GP surgery characteristics in driving patient registration behaviours. This chapter aims to capture this fuller picture of patient registration behaviour, using data derived in Chapter 2, and techniques that have emerged over the previous 2 chapters in order to better develop and understand this linkage. In doing so, multi-level mixed effect logit models are specified in order to capture the structure of access to GP surgeries, and the effects of context at different aggregations.

In doing this, the increased interest in patient choice is first set out with respect to the NHS, providing a backdrop for the importance of understanding the registration behaviours of patients. This is of notable import in an NHS that is constrained by a cost-cutting agenda in Government policy: it is being put under pressure to change its operating practices in order to create savings through efficiency; and is potentially subject to some extreme reforms to the operation of the welfare system as a whole. The discussion of patient choice, and the direction of the proposed reforms bring up some important aspects that could well affect the geography of patient registration in the future. The set of agreed-upon practice boundaries defined by Southwark GP surgeries are analysed. Finally, an outline understanding of hierarchical linear models, also known as multi-level models, is demonstrated before a multi-level analysis of registration in Southwark is undertaken.

7.2 Patient choice in the NHS

7.2.1 Reform in the NHS: a broad perspective

In the middle of 2010, the newly incumbent Conservative-Liberal Democrat UK coalition Government set out— under the ministerial leadership of the Secretary of State for Health, Andrew Lansley— a new vision for the future of the NHS within a White Paper entitled “Equity and excellence: Liberating the NHS”. The elements laid out in the White Paper constituted a radical reform to the administration, management and practice of healthcare under the NHS, and implied changes that challenged the existing understandings of how a welfare state should operate. There is often seen as being a political imperative to engineer positive changes in national wellbeing through the imposed structure of the welfare regime in place: such changes, it could be argued, are mandated by increasing evidence of inequalities in both access to healthcare, and in the health outcomes of different segments of society. Influential reports, most notably the Michael Marmot-chaired review of health inequalities in England: “Fair Society, Healthy Lives” (Marmot Review, 2010), set out the issues facing effective healthcare service, identifying the existence of a social gradient in population health linked to the social stratification of the population itself – essentially: the more deprived a neighbourhood a person lives in; the worse off they are in terms of social standing; the worse the likely health outcomes of that person are, leading to a higher likelihood of premature death.

The realisation as to the existence of a social gradient in health emphasised that reducing health inequalities is not simply a matter of attempting to improve life chances amongst the most severely deprived social groups: rather, any action to reduce health inequalities needs to happen across society as a whole. This is a substantial advance from the position of the Acheson report (1998) which spoke of a health “gap” and the need to improve the health of the “worst off” in society. Despite this, the Acheson report did introduce the value of tackling inequalities in a number of settings: schools, the workplace and the neighbourhood, rather than purely through the interventional sites of the GP surgery, or the Hospital. It is clear that the steepness of the gradient of health inequality needs to be reduced, and to do that any response needs to be proportional to the health circumstances that are found in different neighbourhoods. The Marmot Review emphasises that fairness and social justice are core to tackling health inequalities, but sees their emphasis as differing from the discussion of healthcare equity and social justice in Chapter 1, which considers the responsibilities of the

NHS as an organisation in delivering a service that is perceived as just, shedding light on the potential for structural inequalities in that service. Rather, the Marmot review advocates for a participatory approach to decision-making that empowers individuals and communities to develop more effective local delivery of healthcare and thus reduce health inequalities through the localised realisation of health equity. There has been a considerable amount of recent comment that has revitalised the literature on social justice in this regard, most significantly Wilkinson and Pickett (2009) and Dorling (2010a). Whilst Wilkinson and Pickett act to demonstrate the resounding benefits of a more equal society, it is Dorling (acting with the kind of cynicism usual reserved for David Harvey alone (cf. Harvey, 1973)) who simultaneously signals the end of an era of rising inequalities, whilst failing to announce the beginning of an era of greater equality. Dorling (2010a), however, is correct in his summation of the human condition, the apparatus that created an unequal society will not just be replaced by "the millions of tiny acts required to no longer tolerate the greed, prejudice, exclusion and elitism that foster inequality" (p.318), nonetheless, the identification of inequality as a "social" condition is something that offers some hope for greater equality in the future.

Hand in hand with the articulation of health inequalities, and the requirement for social justice acting at a local level, has gone debate surrounding the social determinants of health, which largely defines the structural differences that have driven rising health inequalities. The World Health Organisation (WHO) established a commission on the social determinants of health (CSDH) in 2005, again chaired by Michael Marmot, which published its report "closing the gap in a generation" (CSDH, 2008), in which numerous inequities in health are described as avoidable, but arise nonetheless due to political, social and economic forces. Dorling (2010b) outlines how local services matter to the quality of an area, arguing that "since at least 1968 in the UK, inequalities in local service delivery have contributed to growing spatial social polarization" (p. 16). The key aspect of much of this literature, even that which exists at a global scale, is the value of local focus, local interventions, local empowerment and engaging communities and individuals.

Returning to the content of the recent NHS white paper, it is clear that ambition to tackle health inequalities underpins the rhetoric of reform. Certainly, a neoliberal agenda that desperately requires cost-savings in public finance, whilst balancing a mandate to be transparent in doing so, disturbs our impression of the purity of such reforms, but healthcare

reforms are themselves a political statement: one only has to look at the US administration's initiative to extend the eligibility and coverage of healthcare insurance in the USA under what has been dubbed "Obama Care". The proposed NHS reforms favour important elements in the discussion of practical responses to tackling healthcare inequalities, first and foremost allowing for greater choice and more control in patients' access to care. In order to make this happen, local services are foregrounded, and given greater autonomy in their ability to make decisions that will benefit patients and local communities. This in turn invokes a greater significance for the role of primary care; both as an equalising force in the quest for a reduction in the slope of the acknowledged social gradient in health outcomes; but also as a direct provider of care in a way that is cost-effective. This in mind, it is impossible to avoid highlighting the role of the "Big Society" in the way that public services are being reformed, certainly "the NHS is an integral part of a Big Society" (DH, 2010b p.7) if the White Paper is to be believed. The intent of "big society" is for the state to foment social renewal through the volunteerism of its citizens, indeed the rhetoric is one of devolution, and the transfer of power from central to local government. The Government uses this as support for its agenda to reduce the impact of the state in people's everyday lives, and move away from what David Cameron (2009) branded a "command and control" impetus in Labour instituted "Big Government". This is manifest through the proposed removal of current statutes which give central Government the capability of intervening in the management of the NHS, with the recent white paper advocating for an NHS with "greater freedoms, clear duties, and transparency" (2010a p. 7). The removal of top-down controls in favour of a bottom-up approach, it is claimed, will put the NHS on a "more stable and sustainable footing, free from frequent and arbitrary political meddling" (2010a p. 9).

Should the Health and Social Care Bill (subject to Parliamentary approval at the time of writing) be enshrined into law, it will abolish the responsibilities of Strategic Health Authorities (SHA) and Primary Care Trusts (PCT), described as "unnecessary tiers of management" (DH, 2011c p.1) in administering, managing and commissioning care, in favour of consortia of GP surgeries and arms-length oversight bodies. Next is a discussion of the patient choice agenda, and the suggestion that it is by no means a new idea: indeed the previous two chapters have suggested that patients in Southwark exhibit a pattern of registration with GP surgeries that deviates from a normative, accessibility-based structure, and shows evidence of diverse registration behaviours amongst the communities of patients

attributable to different GP surgeries. Subsequently, the current state of registration with regard to catchment areas is outlined, as their suggested abolition denotes a major departure in the way that local services are managed.

7.2.2 Patient Choice in NHS primary care

The NHS is increasingly primary care focused, with a health improvement agenda operationalised through local service provision believed to provide better value for money than relatively more expensive hospital services. The NHS constitution, agreed in 2009 with a high degree of cross-party support, outlines the rights that a patient of the NHS can expect, in line with the NHS's commitment to equity and universal service as discussed in Chapter 1. Foremost of interest in the context of this thesis is the following:

"you have a right to choose your GP practice" (DH, 2010a p.7, emphasis in original)

The NHS constitution is clearly set out to transform the role of patient choice in the NHS, with then Labour secretary of state for health Andy Burnham stating the need to "extend further patient choice in primary care" (Burnham, 2009) in a speech to the Kings Fund. This stems from the emergent belief that increased choice has a major role to play in reducing health inequalities, successive NHS white papers under a Labour-led NHS focused directly on this issue from the outset. Both "choosing health" (DH, 2004) and "our health, our care, our say" (DH, 2006), as well as the recent public health white paper "healthy lives, healthy people" (DH, 2010e) prescribe greater choice for patients, and in doing so notions of locality, neighbourhood and community come to the fore. There is an emergent dichotomy in the nature of choice however: between a patient having a right to access healthcare services of their own choosing; and patients choosing to take control of their lifestyle and taking responsibility for their own health as part of the NHS agenda toward "health promotion". The focus here is on the former, although the value of the latter cannot be underestimated in terms of reducing the financial burden the NHS faces in providing interventional healthcare to people suffering obesity-, or smoking-related illnesses, amongst others. Most recently, the "equity and excellence" white paper has stated that any patient should be able to choose or change their GP surgery without being "limited to one that is nearest to [their] home" (DH, 2010b).

The articulation of neighbourhood, communities, and the nebulous conceptualization of "local", as well as the proposed changes to the hierarchical structure of management of the

NHS, demonstrates a loosening of the geographical basis to the organisation of NHS services which has to this point advocated that patients register with geographically proximate GP surgeries. Examples in this regard include the directive that GP surgeries should be “within walking distance for mothers with prams” (Ministry of Health, 1962: source Sumner, 1971). However, whether this was expressly enforced is questionable, with Moon and North (2000) and Corrigan (2005) demonstrating that patient choice has always been an element of primary care provision since the NHS was founded in 1948. In reality, it was the uniform nature of GP services, and the lack of information that existed on any extant differences that led to distance being the most significant determinant of choice of care in the UK NHS. Whilst recent innovations, such as the NHS Choices website (which is intended as a provider of health information for the UK population), have attempted to give people access to the kind of information relevant to inform decision-making with regard to choice of GP surgery, the NHS mandate to provide an equitable service of equal quality to all would seem to undermine choice on the basis of quality. In general, the NHS choices website gives little away beyond ordering local GP services by distance from a user supplied postcode and thus providing some basic geographic context for choice.

In the NHS, distance has been seen as the most important factor in patient choice of GP surgery: several studies in the late 1980s and 1990s highlight its primacy with regard to both registration, and to changing GP surgery (Gandhi et al, 1996; Billingham and Whitfield, 1993; Salisbury 1989). More recently, Exworthy and Peckham (2006) and Greener (2007) have demonstrated the strongly location-based nature of primary care services, emphasising the rarity with which patients travel beyond local services. Despite this, observable differences in patient choice have been demonstrated by looking at patterns of registration and utilisation, with influences echoing the earlier discussion of health inequalities and social determinants of health. The factors evidenced as important in driving patient registration and utilisation are numerous (Hays et al, 1990; Joseph and Phillips, 1984), and are motivated by: the age of both the GP and the patient (Ahmad et al, 1991; Hopkins et al, 1967); the sex of the GP and the patient (Salisbury, 1989); patient social class (Goddard and Smith, 2001); patient and GP ethnicity (Ahmad et al, 1991; Saha et al, 2000), wealth and deprivation (Knox and Pacione, 1980; Knox, 1978) and other locational factors (Bullen et al, 1996). In the US system, “quality”-based factors (Hawthorne and Kwan, 2011) have been shown to be of greater import than is evident in the UK, with the greatest value placed on professional

characteristics such as certification, specialisation and evidence of malpractice, with distance only being of middling importance (Bornstein et al, 2000).

The analysis in this chapter is intended to consider the current nature of choice by using a case study of Southwark, an inner London borough with a high population, and service density. As such it creates an analytical baseline through which to consider the pre-existing structure of choice in GP surgeries, whilst further seeking to quantify associations between patients and GP surgeries as integral to the pattern of patient registration behaviours. Important to this is the issue of catchment areas, which has been seen by the Government as a significant constraint in opening up patient choice. Their suggested abolition signifies Governmental intent with regard to the geographical freedom of patient choice, and these effects with regard to Southwark, are considered in the next section.

7.2.3 GP Surgery Catchment Areas

Reform in the NHS had specified that GP surgery catchment areas were to be abolished in order to extend patient choice. However, the revised GP Contract has simply specified that an “outer boundary” be specified that will be large enough to allow patient to move house and maintain continuity of care (GP Business, 2011). However, a pilot study will take place that tests the practicality of no practice boundaries, so the abolition of catchments may simply have been delayed. A catchment area is a bounded geographical area within which a GP agrees to provide service to a specified number of patients. If this self-imposed limit has been reached the GP surgery is not obliged to provide services to any additional patients. A GP surgery’s patient list may thus be ‘closed’ to new registrants, irrespective of residence, if the practice is functioning at capacity. A patient registered with a GP surgery can expect to be provided with primary care health services, including home visits if required. In this way catchments were intended to regulate GP workload. Registration with a local NHS GP is a right as defined in the NHS Constitution (2009), and in practice catchments are agreed by negotiation between the GP and the NHS. In the urban context, however, available local services can include numerous GP surgeries: in the case of Southwark, for example, many catchment areas defined by GP surgeries: overlap each other; overlap the administrative boundaries of the Borough; may not correspond to the areas where many of their patients live; or may simply be so extensive as to effectively stipulate no catchment at all.

Catchment areas were initially ad hoc inventions of GP surgeries used to impose constraints on the volume of patients they could expect, but were later formalised by the NHS (Martin and Williams, 1991), although they were never really fully implemented in practice. In the case of Southwark, the GP surgery catchment areas were agreed upon with Southwark Primary Care Trust in 2005, with some typical examples shown in Figure 7.1 and 7.2, there are 45 catchments, with 2 GP surgeries failing to provide a catchment area map. The set of catchments are notable for a number of reasons: firstly, they all seem to have been drawn subject to the geometry of the local built environment, particularly the road networks; secondly they all delineate contiguous areas; and thirdly, they are rarely drawn with compactness in mind, as the areas delimited are frequently irregular and apparently include or exclude areas in an arbitrary manner. The complete set of catchment areas for Southwark GP surgeries, minus the unavailable two, were digitised and analysed within a GIS in order to derive a better understanding of the motivation behind their creation.



Figure 7.1: A catchment area defined for a GP surgery in the Peckham area of Southwark.

The map of catchment area overlap for the 45 available Southwark GP surgeries is shown in Figure 7.3. The two missing GP surgeries are located in the centre-north part of the Borough, in spite of this, access to GP surgeries based on the defined GP surgery catchment areas shows a similar pattern of overlap when compared to Figure 6.9 in the previous

chapter, which demonstrates the spatial extent of service areas derived from patient distributions. In order to test this further, the patient distribution for each GP surgery is compared against the catchment area to see whether patients lie outside of the catchment areas, and if so what the characteristics of these patients are.

Southwark GP Practice Catchment Area January 2005

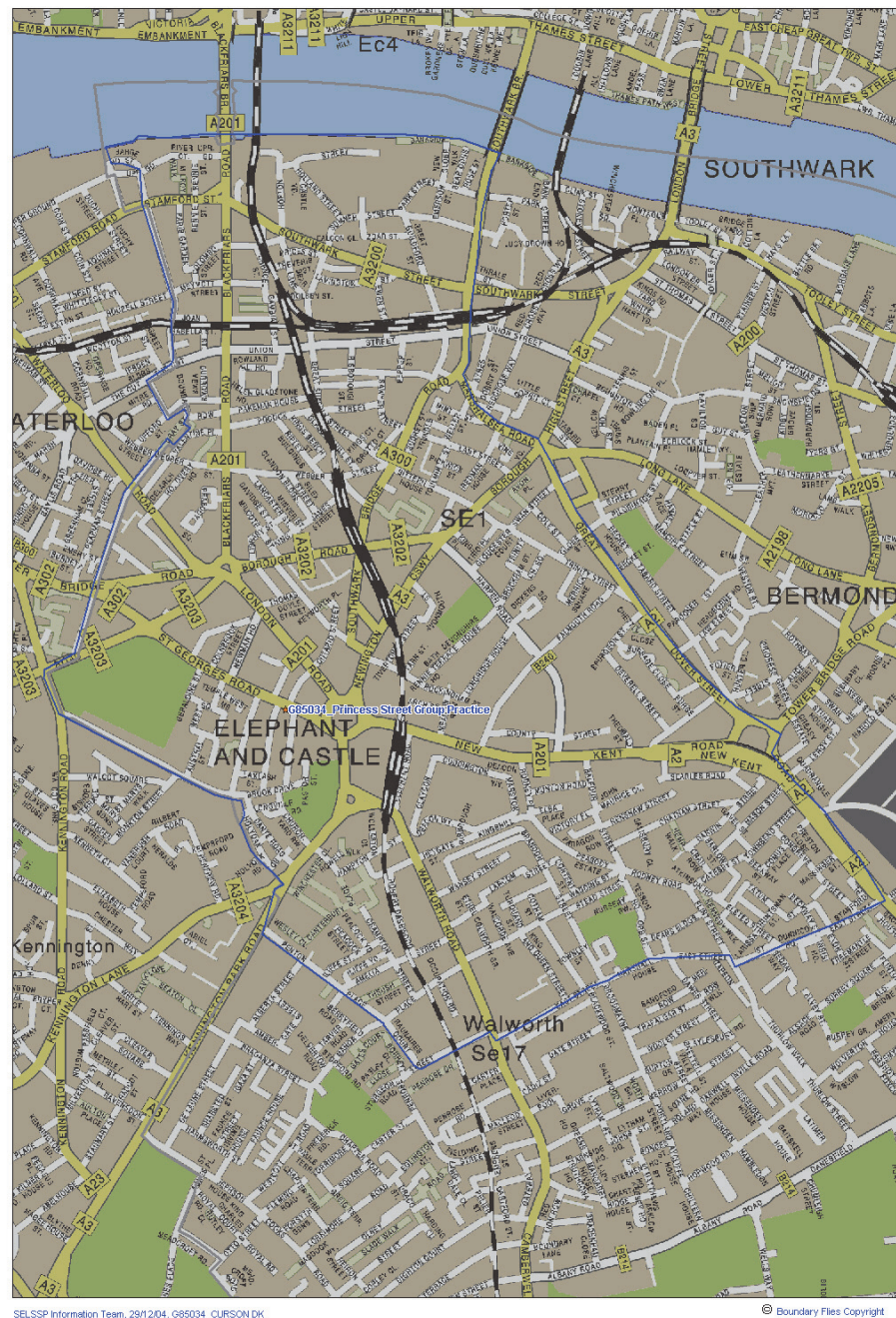


Figure 7.2: A catchment area defined for a GP surgery in the Elephant and Castle area of Southwark.

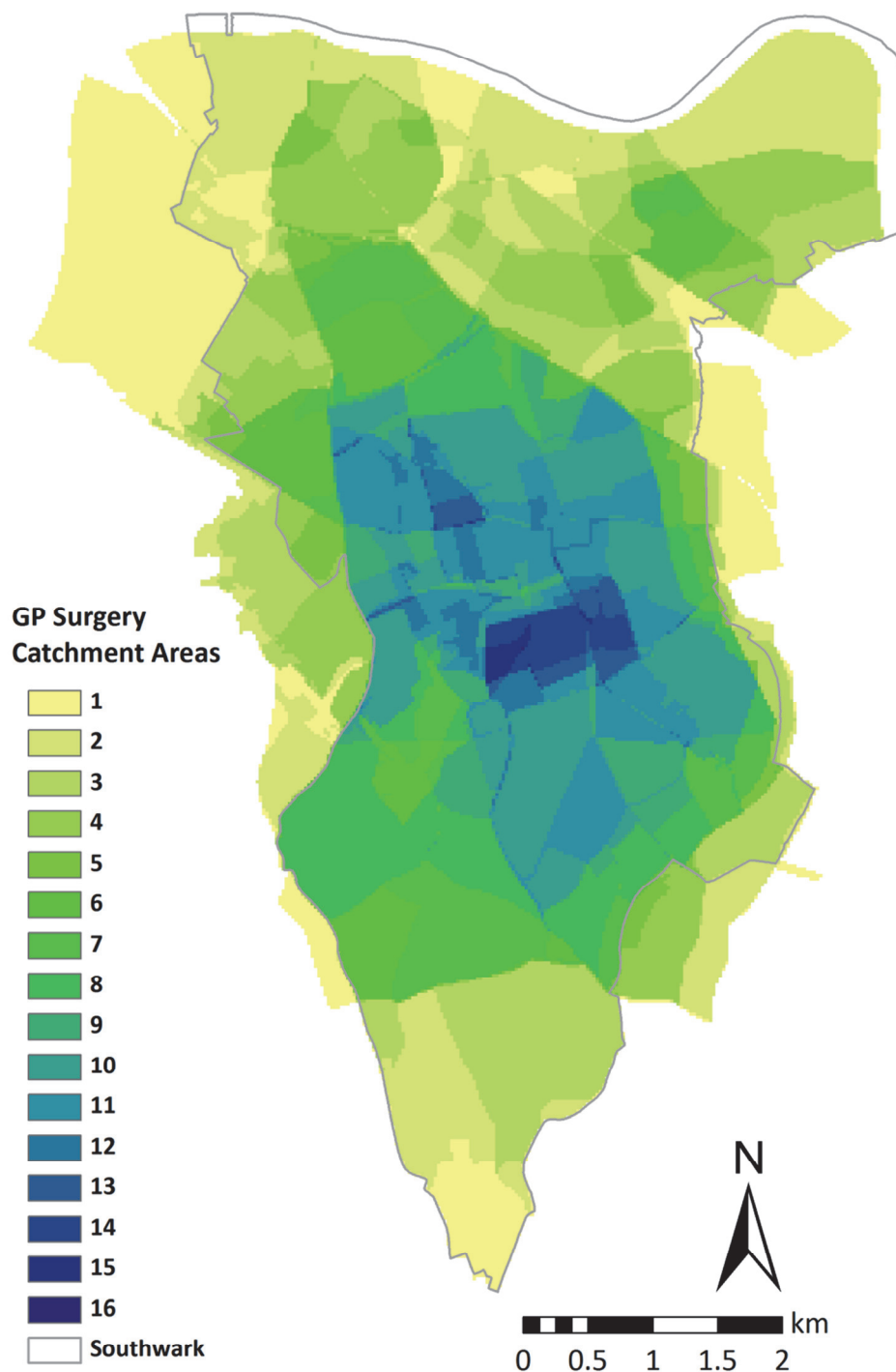


Figure 7.3: Overlapping catchment areas for 45 Southwark GP surgeries.

For an average Southwark GP surgery, 80.4% of its registered patients will reside within its defined catchment area. However, this figure varies from 47% for a GP surgery that has drawn a particularly tightly defined catchment, to 96% for a GP surgery that has specified an extremely general catchment. The range of values for Southwark GP surgeries is shown in the histogram Figure 7.4. In general, there does not seem to have been a consistent

approach to drawing catchment areas, with significant variation in the percentage of registered patients that fall within defined catchments for different GP surgeries. Coupled with this, the overlaps in Figure 7.3 suggest no spatial ordering of service provision, and an essentially ad hoc arrangement of zones.

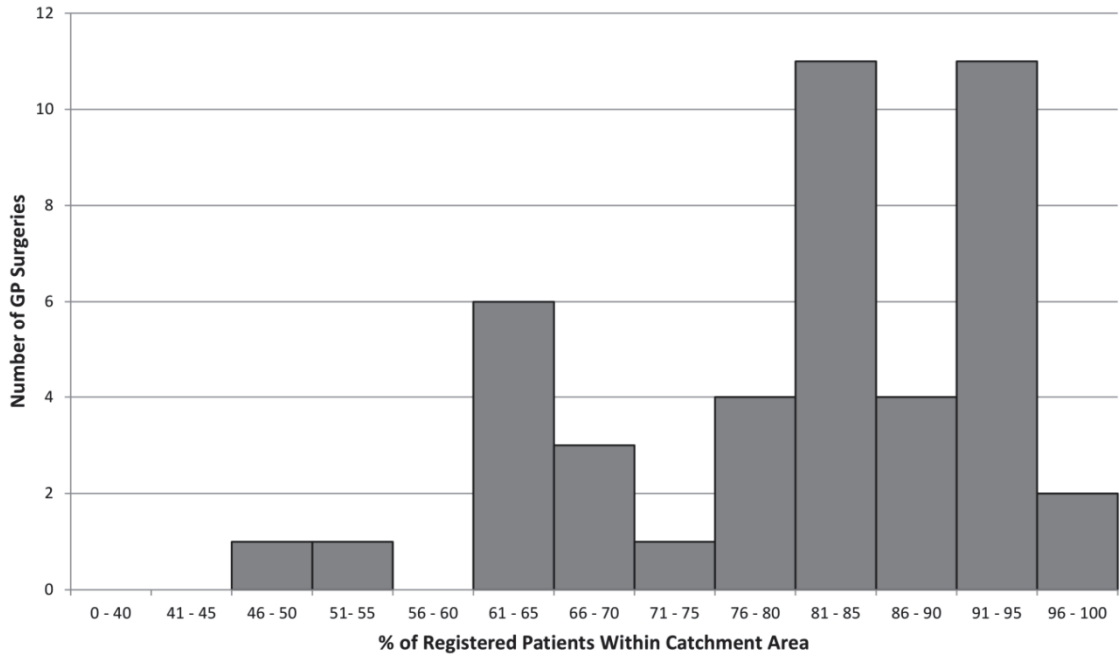


Figure 7.4: Histogram of the percentage of patients within the catchment areas of their registered GP surgery.

For patient sex, age and ethnicity, an index score was calculated comparing the proportion of patients with a given characteristic who lie outside of their GP surgeries prescribed catchment area (the target population), with the total proportion of patients with that characteristic observed in the GP surgery as a whole (the base population), this is given by equation 7.1.

$$I_n = \frac{t_n / \sum_{n=1}^N t_n}{b_n / \sum_{n=1}^N b_n} \times 100 \quad (7.1)$$

Where t identifies a particular characteristic, b is the base, and n refers to a catchment area. The score is scaled up so that 100 represents no difference between target and base in terms of n , with greater than 100 indicating a relative overrepresentation of n in the target, and less than 100 an underrepresentation.

For patient sex, the average index score is 99 for women, and 101 for men, with a standard deviation of 4.8 and 4.5 respectively; there is little to suggest that there is a significant over

or under recruitment of either men or women by GP surgeries. However, as demonstrated in Figure 7.5, the same is not true for the age of patients; the dark coloured bars are skewed to the left, whilst the lighter bars are skewed right indicating that older patients tend to reside disproportionately outside of their GP surgeries catchment area when compared to younger patients. Patients below the age of 16 were excluded as their registration is largely constrained by that of their parents.

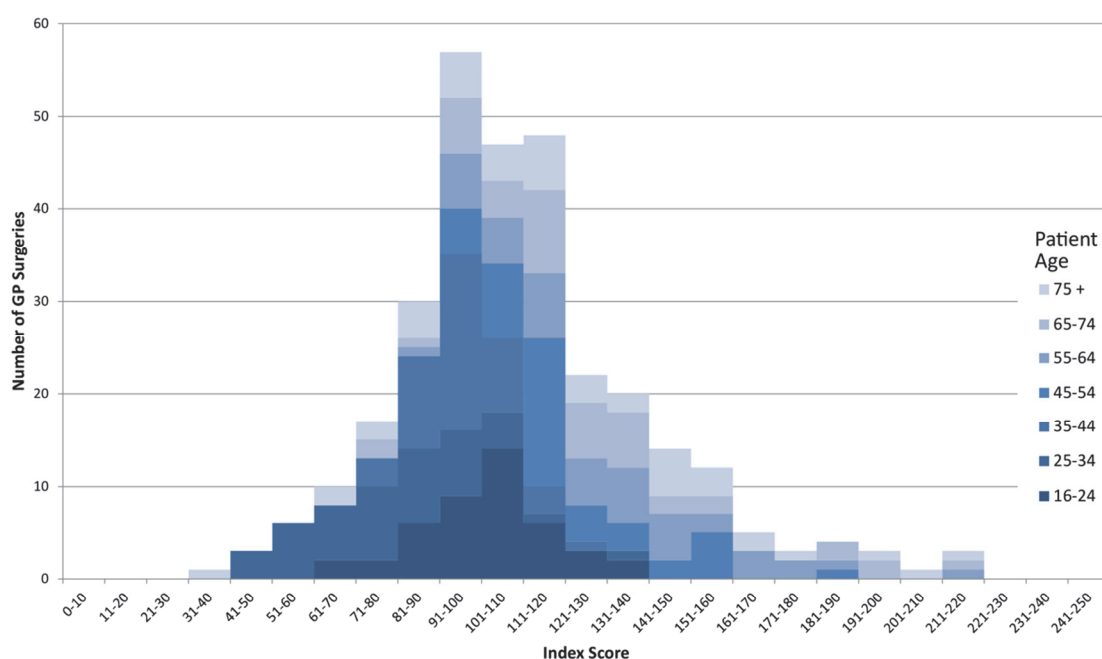


Figure 7.5: Stacked histogram indicating the index score for patients of different age bands lying outside of their GP surgery catchment area. (Unstandardised for the proportion of people in different age groups per GP Surgery).

Patient age seems to suggest a systematic bias in outside-of-catchment registration, this may be accounted for by factors such the length of registration with a GP surgery – the longer you live in Southwark, the more likely you are to have moved from somewhere in the locality, similarly, older patients may have been registered with a GP surgery before catchment areas were formally introduced as a constraint on access. Patient ethnicity produces a more complex picture than patient age, as is evident in the histogram of the indices of patients of different ethnicity lying outside of their GP catchment area (Figure 7.6). Whilst there are some general trends, such as the tendency for British and Muslim patients to be slightly right skewed in the histogram, whilst East Asian and Eastern European patients are more left skewed, the trend are not particularly consistent. What is more in evidence is that all ethnic groups exhibit outliers in terms of index score for a few GP surgeries, this suggests that the effect of GP surgeries registering patients outside of their catchment area

may be more associated with the characteristics of particular GP surgeries, rather than the circumstances of access as might be the case with age.

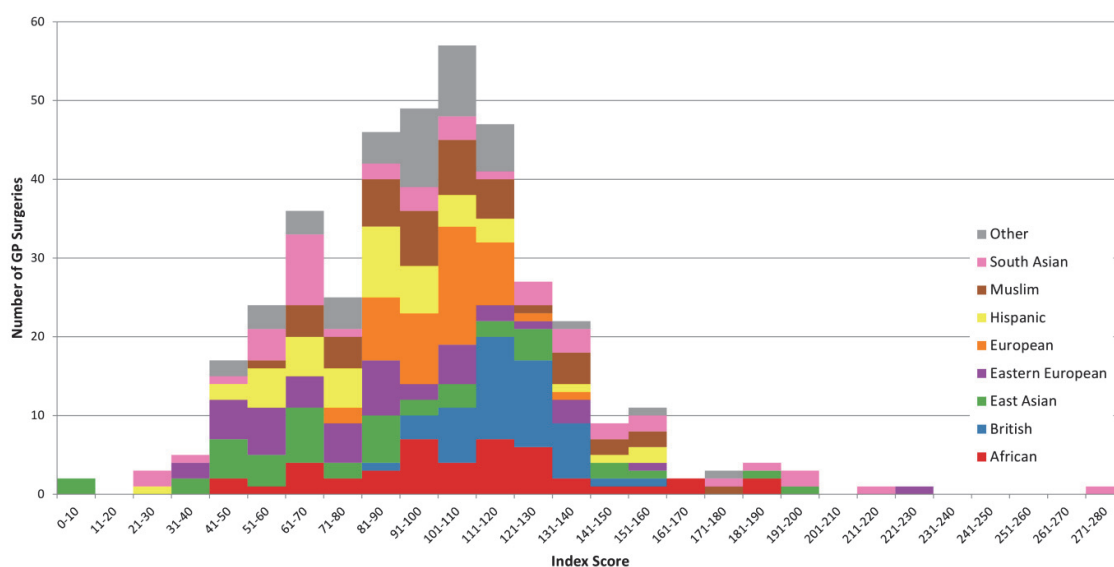


Figure 7.6: Stacked histogram indicating the index score for patients of different ethnicities lying outside of their GP surgery catchment area. (Unstandardised for the proportion of people in different ethnic groups per GP Surgery).

In order to test some of these assumptions, the analysis at this point moves to consider multivariate effects; a logistic regression is specified for patients in which the dependent variable is a binary variable indicating whether a patient lies within the catchment area of their chosen GP surgery or not. The set of independent variables are the patient's sex, age (in the bands in Figure 7.5), ethnicity (by the Onomap categories in Fig. 7.6) and a measure of length of registration derived from the record of the date each patient was registered with their GP surgery. Age is banded because its relationship with the dependent variable is not a straightforward linear one, particularly when interactions are considered in Table 7.2: most importantly banding highlighted the dependence of children and adolescent registrations with those of their parents, but it also highlights a varying relationship between young and middle-aged people, middle aged and people of retirement age, and post-retirement age patients that cannot be accounted by transforming the continuous variable. Keeping the banded age variable in these models is also useful in terms of shared context with the later models of patient behavior, for which the age effects described are even more pronounced.

The data set covers patients accessing the 45 GP surgeries for which a catchment area was reported. The logistic regression is given by equation 7.2.

$$\ln \left[\frac{\text{probability outside catchment}}{\text{probability in catchment}} \right] \\ = \beta_0 + \beta_1 \text{Female} + \beta_2 \text{Age} + \beta_3 \text{Ethnicity} + \beta_4 \text{Age of Registration}$$

(Equation 7.2)

The log odds of a patient residing outside of the catchment area of the GP surgery to which they are registered in expressed in terms of the sex of the patient (Female = 1), the age of the patient (Age: banded as per Figure 7.5, in years), the cultural, ethnic or linguistic origin of the patient (Ethnicity: derived using Onomap as per Chapter 2, 2.3.10), and the length of time that a patient has been registered with their GP surgery (Age of Registration: in years). The age category has a base of patients aged over 75, in order to compare the oldest class of patients with younger ones, again the 0 – 16 year old age category was excluded. The ethnic category has a base of the British group, which has the highest average index value for patients lying outside of their GP surgery's catchment area. The model results are given in Table 7.1.

As anticipated, the logit model shows no significant differences between male and female patients in terms of the likelihood of being registered to a GP surgery and falling outside of that GP's surgery's catchment area. However, the pattern of registration as it pertains to patient age persists, older patients are more likely to be registered to a GP surgeries for which they do not live within the catchment area, patients in age bands 55 - 64 and 65 – 74 years old are not significantly different to patients of age 75 or more, however younger patients are significantly less likely than patients of 75+ years old to be registered to a GP surgery and be outside of that GP surgery's catchment area.

In terms of a patient's ethnicity, the conclusions available in Figure 7.6 are confirmed; all ethnic minority patients are less likely to lie outside of their GP surgeries catchment area than British patients, except for Muslim patients for whom there is no significant difference. Finally, the number of years that a patient has been registered with their GP surgery is found to be highly significant, suggesting that patients who have been registered for longer with their GP surgery are more likely to reside outside of its catchment area.

<i>Variable</i>	Coefficient	Std. Error	z	P> z
Patient Sex (Female)	-0.00670	0.0104	-0.65	0.519
<i>Age of Patient</i>				
16 – 24	-0.253	0.0267	-9.49	0.000
25 – 34	-0.489	0.0254	-19.24	0.000
35 – 44	-0.334	0.0253	-13.21	0.000
45 – 54	-0.0869	0.0258	-3.37	0.001
55 – 64	0.0267	0.0277	0.96	0.335
65 – 74	0.0555	0.0304	1.82	0.068
(base category for age is 75 + years old)				
<i>Ethnicity of Patient</i>				
African	-0.0576	0.0180	-3.19	0.001
East Asian	-0.458	0.0362	-12.66	0.000
Eastern European	-0.221	0.0383	-5.75	0.000
European	-0.151	0.0157	-9.67	0.000
Hispanic	-0.301	0.0313	-9.63	0.000
Muslim	-0.00708	0.0187	-0.38	0.705
South Asian	-0.209	0.0410	-5.1	0.000
Other or Unclassified	-0.180	0.0297	-6.05	0.000
(base category for ethnicity is British)				
Years of Registration with GP Surgery	0.0360	0.000921	39.1	0.000
Constant	-1.30	0.0246	-52.79	0.000
Number of Obs = 247111			Log Likelihood = -118622.45	
LR Chi2(16) = 4304.85			Prob > chi2 = 0.0000	

Table 7.1: Logit Regression results testing characteristics of patients who lie outside the catchment area of their GP surgery.

Given the significance of the years of registration variable, interactions were checked for; no interaction was found with ethnicity, but a significant interaction between years of registration and patient age was found. This means that one variable has an effect on the other, or vice versa, in this case it is likely that there is an interaction between patient age and years of registration as older patients have the opportunity to be registered with a GP surgery for longer owing to their age. In a sense, the effect of length of registration on whether a patient resides outside of a catchment area or not is being moderated by the patient's age. Table 7.2 demonstrates the results for this model, including interaction terms. A likelihood ratio test indicates that the model with interactions is a significantly better model than the model without interactions.

<i>Variable</i>	Coefficient	Std. Error	z	P> z
Patient Sex (Female)	-0.00236	0.0104	-0.23	0.820
Years of Registration with GP Surgery	0.0119	0.00279	4.28	0.000
<i>Age of Patient</i>				
16 – 24	-0.494	0.0354	-13.93	0.000
25 – 34	-0.746	0.0333	-22.42	0.000
35 – 44	-0.557	0.0337	-16.51	0.000
45 – 54	-0.259	0.0346	-7.48	0.000
55 – 64	-0.0824	0.0373	-2.21	0.027
65 – 74	-0.0432	0.0405	-1.07	0.286
<i>Interaction between patient age and years of registration with GP surgery.</i>				
16 – 24 Interaction	0.0366	0.00375	9.76	0.000
25 – 34 Interaction	0.0468	0.00385	12.15	0.000
35 – 44 Interaction	0.0336	0.00359	9.37	0.000
45 – 54 Interaction	0.0233	0.00340	6.84	0.000
55 – 64 Interaction	0.0139	0.00366	3.8	0.000
65 – 74 Interaction	0.0126	0.00389	3.24	0.001
(base category for age is 75 + years old)				
<i>Ethnicity of Patient</i>				
African	-0.0558	0.0180	-3.09	0.002
East Asian	-0.449	0.0362	-12.39	0.000
Eastern European	-0.201	0.0384	-5.23	0.000
European	-0.145	0.0157	-9.25	0.000
Hispanic	-0.292	0.0313	-9.35	0.000
Muslim	-0.00586	0.0187	-0.31	0.754
South Asian	-0.199	0.0410	-4.86	0.000
Other or Unclassified	-0.171	0.0297	-5.75	0.000
(base category for ethnicity is British)				
Constant	-1.126	0.0306	-36.77	0.000
Number of Obs = 247111			Log Likelihood = -118509.05	
LR Chi2(16) = 4531.65			Prob > chi2 = 0.0000	

Table 7.2: Logit Regression results testing characteristics of patients who lie outside the catchment area of their GP surgery, including significant interactions.

The interaction between patient age and years of registration indicates that within any age group, a longer period of registration increases the likelihood of a patient residing outside of their GP surgery's catchment area. However, age on its own is still significant as a patient's age constrains the maximum number of years of registration that they could have with a GP surgery. Older patients are more likely to have lengthy registrations with GP surgeries, and are more likely to live outside of their GP surgery's catchment.

There are several ways that these results could be interpreted; firstly, they may suggest that patient's value continuity of care, choosing to continue with GP surgeries having moved house because they wish to remain with a GP with whom a bond has been formed. Secondly, the pattern of extra-catchment area registration may also reflect registration from before a time when catchments were either imposed, or enforced. Thirdly, older patients may have registered with a GP surgery in a system that has subsequently densified with the addition of new GP surgeries; unfortunately historical data were not available to test this. The interaction between age and registration length is very difficult to separate out in a cross-sectional study, registration length is a cohort effect and a better understanding of it with respect to patient age could only come from a longitudinal dataset. However, in the context of the model in Table 7.2, the interaction between length of registration and age of the patient speaks to the moderating effect of age on length of registration – comparative to the 75+ age group, length of registration has a bigger influence on younger patients than older patients because the relative effect of a few more years of registration is larger for younger patients. It could tentatively be suggested that this is particularly important if the patient is of an age where they may be moving house, as a result of increased income, or family commitments (the coefficient for interaction is largest for the 25-34 year old group), but may choose to retain their GP surgery registration.

Whilst the age component of registration outside of catchment areas seems to be a systematic effect related to the patient's length of registration with a GP surgery, there is little to suggest what is happening with respect to patient ethnicity. The next section will attempt to unpick the ethnic dimension by introducing GP surgery-level effects within a multi-level modelling framework.

7.2.4 Consolidation

This section has introduced the emergent reform agenda in the NHS, a reform agenda which was introduced in the "equity and excellence" white paper and, at the time of writing, remains a contested topic. Key to these proposed reforms is the extension of patient choice, with a symbolic cornerstone being the removal of GP surgery catchment areas. A study of GP surgery defined catchment areas for Southwark has shown that there are patient age and ethnic components to whether a patient lies within the catchment area of their registered GP surgery. The association between extra-catchment area registration and age seems to be mediated by the patient's length of registration with their GP surgery; however,

the ethnic association is not. There is not a significant relationship between patients belonging to different ethnic groups and their length of registration on whether they reside outside of their GP surgery's catchment area; this may suggest that registration behavior is somewhat more premeditated for minority ethnic groups than may be true of British patients. As it transpires, registration behavior for ethnic groups is found in the next section to be associated with the ethnicity of the GPs available at a given GP surgery.

In the next section, multi-level modeling is introduced as a way of assessing the effect of changes in context across the different GP surgeries in Southwark. Contextual effects at the GP surgery model are introduced into the logit model expressed in Table 7.2 in order to better understand the ethnic component to registration. Subsequently, a multilevel model of patient registration behaviour is examined, weighing the effect of distance alongside patient-level and GP surgery-level effects in seeking to explain, in part, how patients choose GP surgeries.

7.3 Multi-level Modeling in Health and Medical Geography

7.3.1 Introduction

The justification for multi-level modeling (MLM), also known as hierarchical or nested modeling (amongst others), is simple: phenomena of observation often fall into groups. In the case of this thesis the possibilities for grouping is broad, but in particular individuals can be grouped by the GP surgery that they use, or by the household that they live in. If individual patients are to be grouped by GP surgery, we cannot assume that the grouping itself was random and we have to allow for the possibility that there are reasons held in common amongst that group as to why they use the same GP surgery. The assumption that patients in a GP surgery are subject to dependence within groups is likely to have some explanatory power (Rabe-Hesketh and Skrondal, 2008; Goldstein et al, 2004; Snijders and Bosker, 1999).

Gatrell and Elliott (2009) show that estimating individual smoking behaviour using simple linear regression fails to account for the variation in smoking behaviours by place. Using MLM, not only can this place-based variation be accounted for, allowing for some places to have higher overall levels of smoking, but also random variations between smoking behaviours and explanatory variables, such as age, that exist across place can also be

explored. Gatrell and Elliot (2009) demonstrate these possible models in Figure 7.7, in which age is plotted against cigarette consumption. Figure 7.7A demonstrates a simple linear regression in which a single model is fitted, but that does not capture the differences in smoking in different places. However, the random intercept model in Figure 7.7B allows for individual estimates for the intercept of each place to be made, effectively demonstrating the variation across places in cigarette consumption by age. Finally Figure 7.7C demonstrates a random slope model in which, in addition to the random intercepts for places, a different relationship (or indeed no relationship) is permitted for each place.

Jones and Duncan (1995) discuss the importance of place differences in understanding chronic illness under the remit of assessing “individuals and their ecologies”. The key question that is asked in this respect pertains to the ecological fallacy: “inappropriate inference from aggregate data about the characteristics of individuals” (Longley et al, 2011 p. 170), Jones and Duncan state that “aggregate results do not mean that relationships hold at the individual level” (1995 p. 28), and that MLMs are an effective way of testing this. Similarly, it is suggested that modeling approaches that do not give appropriate relevance to ecological contexts, choosing instead to focus solely on individual-level data, could be subject to the atomistic fallacy, in which “the individual is considered in isolation from his or her environment” (Longley et al, 2011 p. 170).

The way in which these place-based effects, or hierarchies, are modeled needs further consideration, requiring the unpacking of the differences between fixed and random effects models. Rabe-Hesketh and Skrondal (2008) approach this by highlighting the need to be specific about the “target of inference”: that is, whether interest is in the groups (or places) as part of a larger population of groups, or solely in the distinct groups themselves within the dataset. If groups are to be viewed as being sampled from a larger population, then random effects are prescribed, whereas if the focus of interest is on the particular dataset itself then fixed-effects should be used. Diez-Roux (2000) demonstrates this further, showing how a mixed-effects approach is important to fully understanding group-level and individual-level variables, and consists of “a fixed part that is unchanging across groups... and a random part... that is allowed to vary from group to group” (p. 175). Diez-Roux thus states that the underlying assumption is that “group-specific intercepts and slopes are random samples from a normally distributed population of group-specific intercepts and slopes” (2000 p. 175) whereas individuals are fixed, but can have varying slopes across

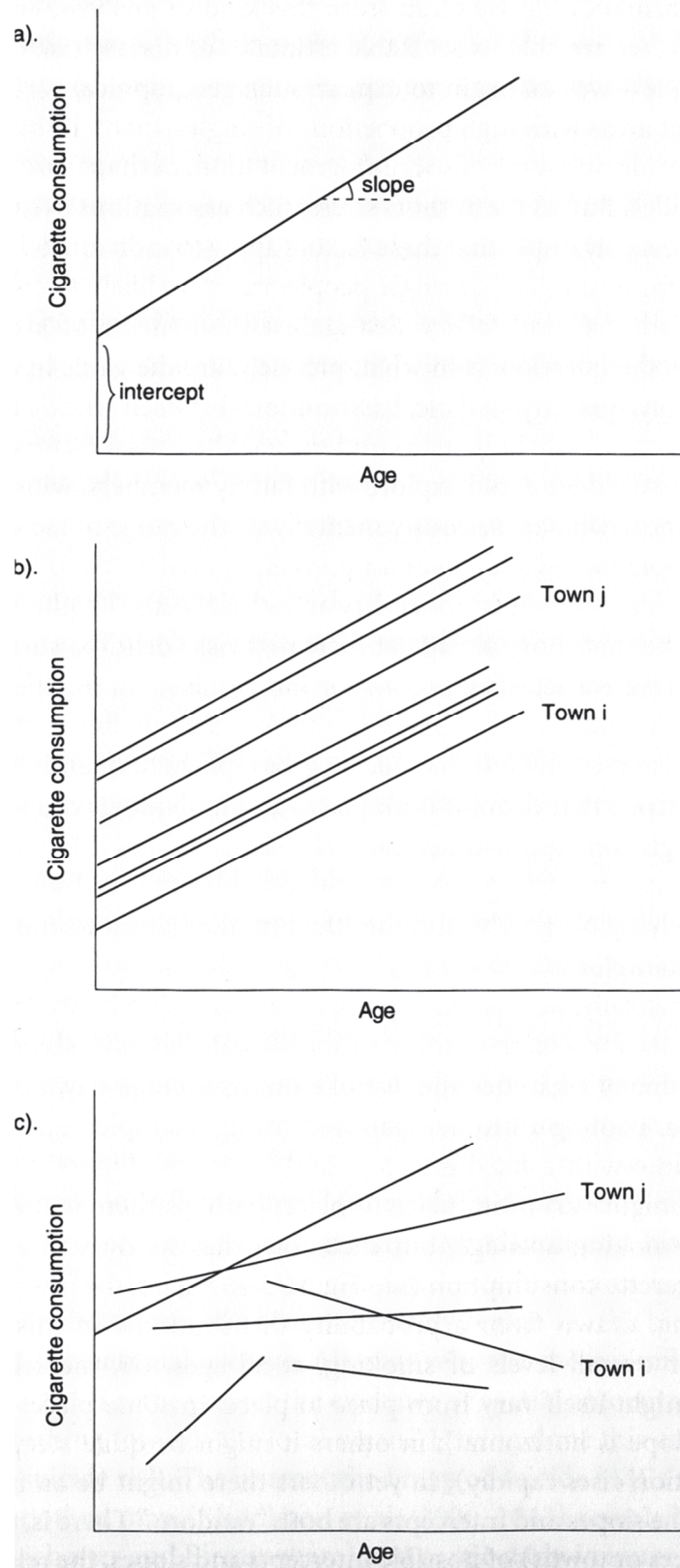


Figure 7.7: Multilevel modeling of hypothetical data
(source: Gatrell and Elliot, 2009 Figure 3.4 p. 60)

groups. This means that we can only draw conclusions about individuals within our dataset – it would be inappropriate to make inferences outside of this sample. Using the example of patients in GP surgeries in this thesis, there might be interest in using fixed-effects to estimate the independent effects of individual-level variables, and the interaction between individual-level effects and group-level effects, on individual outcomes; whilst at the same time accounting for the random-effect of context at the group-level. This tells us something about how Southwark patients register with GP surgeries, but it will be specific to Southwark patients.

Multilevel models are complex, and difficult to explain in the abstract, thus in the next sections, multi-level models are developed in order to explore two aspects of registration behaviour, firstly, the logit model of patients outside of their GP catchment area from the previous section is expanded to include GP level variables, and secondly a more complex model of patient registration behaviour is explored.

7.3.2 A multilevel model pertaining to GP surgery catchments

The logit model described previously for the likelihood of patients of residing outside of the catchment area of their GP surgery is rebuilt within a multi-level framework. Initially, an “empty” model is created in order to explore the variation of the likelihood of patients of residing outside of the catchment area of their GP surgery, by GP surgeries. This is a two-level model with patients nested in GP surgeries in which there are random intercepts for GP surgeries. The model is given by equation 7.3 and the results are summarized in Table 7.3.

$$\text{logit}(P(\text{Outside Catchment})_{ij}) = \beta_0 + u_{0j} \quad (7.3)$$

in which the intercept β_0 is shared by all GP surgeries, and u_{0j} is a random effect that is specific to GP surgery j . The random effect allows the different GP surgeries to have different intercepts for the likelihood of a patient lying outside of its catchment area. Table 7.3 demonstrates that this is important as there appears to be significant between-GP surgery variance. The model suggests that the log-odds of a patient being registered with a GP surgery within whose catchment area they do not lie, on average, is -1.59, but for a particular GP surgery the variance is 0.722. This effectively confirms that for any given GP surgery it is always a minority of patients who lie outside of the catchment area, but that the size of this minority varies by GP surgery.

Variable	Coefficient	Std. Error	z	P> z
Constant	-1.59	0.127	-12.50	0.000
Random-Effects	Estimate	Std. Error		
GP Surgery:				
Variance	0.722	0.153		
Number of Obs = 247111			Log likelihood = -110235.23	
Number of Groups = 45			LR test vs. logistic regression:	
Obs/Group (min,avg,max) = 1528, 5491.4, 18101			chibar2(01) = 21079.29 (0.000)	

Table 7.3: Empty (Null) multilevel model for patients living outside of their GP surgery's catchment area

Plotting the estimated residuals for GP surgeries gives Figure 7.8. As expected there is significant variation about the average, indicating that the number of patients living outside of their catchment areas can vary from significantly above- to significantly below average depending on the GP surgery.

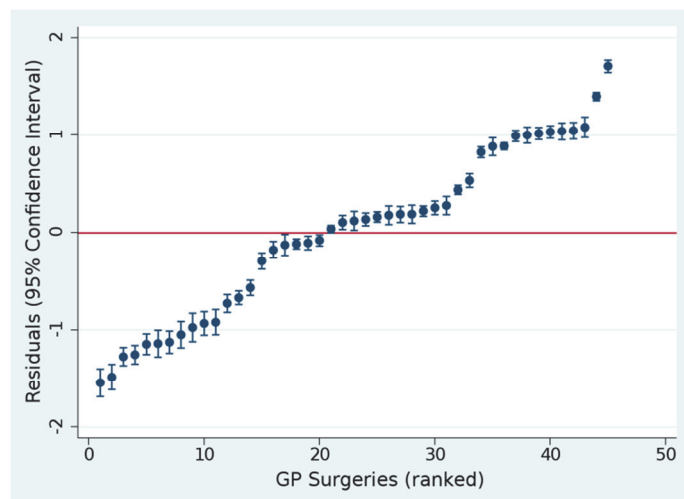


Figure 7.8: Estimated Residuals for 45 GP Surgeries (those that have defined catchment areas) in Southwark.

Individual-level fixed effects are added to the multi-level model in Table 7.3, and two models are created, Model 1 is the multilevel specification of Equation 7.2, whilst Model 2 adds the interaction term discussed as a result of Table 7.2. The multilevel results for these two models are summarised in Table 7.4. The equation for Model 1 is given by:

$$\text{logit}(P(\text{Outside Catchment})_{ij}) = \beta_0 + \beta_1 \text{Sex}_{ij} + \beta_2 \text{Age}_{ij} + \beta_3 \text{Ethnicity}_{ij} + \beta_4 \text{RegYears}_{ij} + u_j$$

where $u_j \sim N(0, \sigma_u^2)$ (7.4)

	Model 1		Model 2	
<i>Variable</i>	Coefficient	Std. Error	Coefficient	Std. Error
Patient Sex (Female)	0.00434	0.0109	0.00878	0.0109
Years of Registration with GP Surgery	0.0394***	0.00113	0.0110***	0.0029
<i>Age of Patient</i>				
16 – 24	-0.203***	0.0282	-0.495***	0.0371
25 – 34	-0.430***	0.0269	-0.711***	0.0349
35 – 44	-0.279***	0.0268	-0.541***	0.0354
45 – 54	-0.0514	0.0273	-0.258***	0.0363
55 – 64	0.0379	0.0293	-0.103**	0.0391
65 – 74	0.0577	0.0321	-0.0370	0.0424
<i>Interaction between patient age and years of registration with GP surgery.</i>				
16 – 24 Interaction			0.0459***	0.00391
25 – 34 Interaction			0.0501***	0.00404
35 – 44 Interaction			0.0405***	0.00375
45 – 54 Interaction			0.0287***	0.00355
55 – 64 Interaction			0.0187***	0.00381
65 – 74 Interaction			0.0121**	0.00404
(base category for age is 75 + years old)				
<i>Ethnicity of Patient</i>				
African	-0.137***	0.0193	-0.134***	0.0193
East Asian	-0.455***	0.0379	-0.444***	0.0379
Eastern European	-0.268***	0.0399	-0.247***	0.0400
European	-0.177***	0.0164	-0.170***	0.0164
Hispanic	-0.372***	0.0327	-0.362***	0.0327
Muslim	-0.125***	0.0199	-0.123***	0.0199
South Asian	-0.146***	0.0427	-0.137***	0.0428
Other or Unclassified	-0.248***	0.0311	-0.239***	0.0311
(base category for ethnicity is British)				
Constant	-1.48***	0.129	-1.28***	0.130
<i>Random-Effects</i>				
	Estimate	Std. Error	Estimate	Std. Error
GP Surgery:				
Variance	0.716	0.151	0.717	0.152
No. of Obs = 247,111	Log likelihood = -108375.5		Log likelihood = -108241.93	
Number of Groups = 45				
Obs/Group	LR test vs. logistic regression:		LR test vs. logistic regression:	
min,avg,max	chibar2(01) = 20493.88 (0.000)		chibar2(01) = 20534.23 (0.000)	
1528, 5491.4, 18101				

Table 7.4: Multilevel models replicating Table 7.1 (model 1) and 7.2 (model 2). * p<0.05, ** p<0.01, *** p<0.001

In Model 1 (Table 7.4), age and ethnicity are categorical variables (and hence would require more coefficients than shown in Equation 7.4: they are not included for simplicity), the interaction between age and years of registration in Model 2 (Table 7.4) would simply involve adding an interaction term to the equation (7.4). The addition of the interaction term

was tested again using a multilevel framework as there is no reason to expect that the significant interaction would simply be reproduced within the multilevel framework.

The models in Table 7.4 offer similar conclusions to the single level logit results in Tables 7.1 and 7.2, but the inclusion of random intercepts for GP surgeries causes some differences in the estimated coefficients, most notably amongst patient ethnicity. This is because the coefficients relate to an “average” GP surgery. Contrary to the results of the standard logit model, all ethnic groups are significantly different to the British group: similarly there are some differences in the significance of some of the age classes, however the interpretation offered previously is still applicable. Comparing the models in Table 7.4, with the empty model in Table 7.3 shows that the individual level variables do not really account for any of the variance at the GP surgery-level. This is expected, however, there may be effects to be accounted for at the GP level in terms different relationships between patient characteristics and residing within catchment areas, so random slope effects are also investigated.

There is no significant variation by patient sex across GP surgeries in terms of patients living outside the catchment areas, although the other patient-level variables raised numerous computational challenges when also specified as a random variable at the GP surgery level. These included the non-concavity of the optimization function, requiring the simplification of the model. In addition, the length of time taken to compute, or attempt, an optimisation of the log likelihood function meant that the Laplacian approximation was used as opposed to the recommend “adaptive Gauss-Hermite quadrature”. This was an important compromise; adaptive Gauss-Hermite quadrature uses multiple integration points (“abscissas”) in order to increase the accuracy of approximation of the log likelihood of a given model, however “computation time increases as a function of the number of quadrature points raised to a power equaling the dimension of the random-effects specification” (StataCorp, 2009 p245). Using the Laplacian approximation, which is effectively adaptive Gauss-Hermite quadrature with only 1 integration point, meant that computation times could be reduced significantly to only a few days for each model, however the use of the Laplacian approximation method means that parameter estimates tend to exhibit more bias than they might otherwise (Pinheiro and Chao, 2006). Nonetheless, a final model for catchment areas was specified as per equation 7.5.

<i>Variable</i>	Coefficient	Std. Error	z	P > z
Patient Sex (Female)	0.00866	0.0109	0.79	0.427
Years of Reg. with GP	0.0113	0.00290	3.88	0.000
Prop. Ethnic Minority GPs	0.00117	0.00375	0.31	0.756
<i>Age of Patient</i>				
16 – 24	-0.490	0.0371	-13.2	0.000
25 – 34	-0.706	0.0349	-20.2	0.000
35 – 44	-0.538	0.0354	-15.2	0.000
45 – 54	-0.256	0.0363	-7.05	0.000
55 – 64	-0.100	0.0391	-2.56	0.011
65 – 74	-0.0375	0.0424	-0.88	0.377
<i>Interaction between patient age and years of registration with GP surgery.</i>				
16 – 24 Interaction	0.0454	0.00392	11.59	0.000
25 – 34 Interaction	0.0495	0.00404	12.26	0.000
35 – 44 Interaction	0.0403	0.00375	10.76	0.000
45 – 54 Interaction	0.0286	0.00355	8.05	0.000
55 – 64 Interaction	0.0185	0.00381	4.84	0.000
65 – 74 Interaction	0.0120	0.00405	2.97	0.003
(base category for age is 75 + years old)				
<i>Ethnicity of Patient</i>				
African	-0.374	0.0421	-8.88	0.000
East Asian	-0.655	0.0743	-8.82	0.000
Eastern European	-0.246	0.0783	-3.14	0.002
European	-0.234	0.0322	-7.27	0.000
Hispanic	-0.411	0.0644	-6.39	0.000
Muslim	-0.455	0.0433	-10.49	0.000
South Asian	-0.253	0.0869	-2.91	0.004
Other or Unclassified	-0.356	0.0626	-5.68	0.000
<i>Interaction between Patient Ethnicity and proportion Ethnic Minority GPs in GP Surgery</i>				
African Interaction	0.00411	0.000620	6.65	0.000
East Asian Interaction	0.00405	0.00124	3.36	0.001
E. European Interaction	-0.00000801	0.00129	-0.01	0.995
European Interaction	0.00125	0.000540	2.34	0.019
Hispanic Interaction	0.000940	0.00104	0.9	0.367
Muslim Interaction	0.00563	0.000640	8.86	0.000
South Asian Interaction	0.00221	0.00138	1.6	0.109
Other/Unclass. Interact.	0.00220	0.000991	2.23	0.026
(base category for ethnicity is British)				
Constant	-1.37	0.276	-4.96	0.000
<i>Random-Effects</i>				
	Estimate	Std. Error	Estimate	Std. Error
GP Surgery:				
Variance (Prop Eth GPs)	0.0000674	0.00023		
Variance	1.11957	0.75129		
Covariance	-0.00616	0.0145		
Number of Obs = 247111			Log likelihood = -108170.73	
Number of Groups = 45				
Obs/Group (min,avg,max)			LR test vs. logistic regression:	
(1528, 5491.4, 18101)			chibar2(3) = 20461.6 (0.000)	

Table 7.5: Multilevel Model results for patients living outside of their GP surgery catchment areas, with fixed and random effects and a cross-level interaction.

$$\begin{aligned}
& \text{logit}(P(\text{Outside Catchment})_{ij}) \\
&= \beta_0 + \beta_1 \text{Sex}_{ij} + \beta_2 \text{Age}_{ij} + \beta_3 \text{Ethnicity}_{ij} + \beta_4 \text{RegYears}_{ij} \\
&+ \beta_5 \text{Age}_{ij} \text{RegYears}_{ij} + \beta_6 \text{GP Ethnicities}_j + \beta_7 \text{Ethnicity}_{ij} \text{GP Ethnicity}_j + u_j
\end{aligned}
\tag{7.5}$$

In this model, the interaction between patient age and years of registration is retained, but a GP surgery level variable –the percentage of GPs in the GP Surgery of minority ethnicity – is added. A cross-level interaction between patient ethnicity and GP ethnicity is also specified. The results are given in Table 7.5.

The interpretation of the results in Table 7.5 is the same as discussed previously except for the introduction of the interaction between patients by ethnic group and the proportion of ethnic minority GPs at a GP surgery (in which an ethnic minority is specified as not belonging to the British, Eastern European, Hispanic or European groups). The patient ethnicity variable remains the same, demonstrating that each ethnic group is significantly less likely to reside outside of their registered GP surgery's catchment area than the British group. However, when taking into account the ethnicity of the GPs at each surgery, there seems to be a strong effect for African, Muslim and East Asian patients that suggests that their likelihood of residing outside of their GP surgery catchment area is raised relative to the British group when there is a higher proportion of ethnic minority GPs at that surgery. This is also true, albeit to a lesser extent for the European and Other group, whilst the remaining groups are not significantly different to the British group.

In summary, there seems to be an age and an ethnicity component to patients being registered with a GP surgery but living outside of its catchment area. The age component is associated with the age of a patient's registration, with older patients likely to have been registered with a GP surgery for a longer period of time, and who hence may have avoided the imposition of catchment area regulations in the past. Having said this, it is unclear whether catchment areas were strictly enforced in the past, with discretion seeming to lie with the individual GP surgery. Similarly, the ethnic component may in part be explained by the ethnicity of the GPs at a given surgery, it seems that some patients in particular ethnic groups, such as African, East Asian and Muslim patients, are more likely to reside outside of their GP surgery's catchment area if the GPs employed tend to be from a minority ethnicity

background. Certainly, the results for the ethnicity component hint at the existence of patient choice on this basis within Southwark, and can be seen as a precursor to the fuller examination of patient registration behaviour in the next section.

7.3.3 Exploring Patient Registration Behaviours

Lewis and Longley (in press) explore the socio-demographic and geographic characteristics of patient registration behaviour in Southwark, using the condition of whether a patient uses their nearest GP surgery or not as an indicator of patient choice. Variables associated with choice are assessed using a logit model. However, there are several assumptions in their paper that can be explored further in this thesis.

Firstly, Lewis and Longley (in press) use distance measured on the road network in order to derive the nearest GP surgery for each patient; in this thesis travel time is also considered. Secondly, GP surgeries are assumed to have an unconstrained capacity in the Lewis and Longley paper when deriving the nearest GP surgery by network distance. This may be unrealistic in reality. In this thesis, an indication of a patients nearest GP surgery is also derived subject to capacity constraints using the GP surgery market areas derived in Chapter 5 (5.4). Thus the conclusions drawn in Lewis and Longley are also tested subject to constrained GP surgery capacities for network distance and public transport travel time. Thirdly, the Lewis and Longley paper uses a straightforward logit model approach which does not account for variation at the GP surgery level, therefore a multilevel modeling approach is also demonstrated to account for the potential for GP surgery level effects not previously handled. In the first instance, Table 7.6 demonstrates results for four logit specifications, in which model 1 is an analogue of the model in Lewis and Longley, model 2 uses travel time, with unconstrained GP surgery capacities, and models 3 and 4 use constrained GP capacities for network distance and travel time respectively.

The explanatory variables are as follows: distance to nearest GP surgery (either network distance, or travel time), number of locally accessible GP surgeries, number of GPs at nearest surgery, patient years of registration with GP surgery, patient sex, patient age, patient ethnicity, proportion of ethnic minority GPs at nearest GP surgery.

The number of locally accessible GP surgeries is defined using the GP surgery service areas derived for Southwark GPs in Chapter 6, using the 80 percent volume contours. This is a slightly different from the results reported by Lewis and Longley paper which supports the

use of 75% contours with reference to Shortt et al (2005). The 80% value used here derives from findings in the previous chapter (6.4.2). The rationale for using the number of service areas that a patient falls within as a marker of the number of locally accessible GP surgeries derives from Fotheringham's (1983) ideas of competing destinations. However rather than exercising it using a spatial interaction model, as Fotheringham does, here it indicates the set of potential GP surgeries that patients could access by virtue of the registration patterns of their neighbours. Basically, if an area is delineated as part of a GP surgery's service area, then it indicates that some patients of that GP surgery are within that service area; as the service area is constrained to be the smallest area that contains 80% of the patients of the GP surgery, and GP surgeries, as location based services, have relatively tightly defined service areas at the 80% interval, we assume that that GP surgery represents a viable GP surgery for patients that are within its service area. Therefore the number of service areas that a patient lies within represents the number of viable GP surgeries that a patient has access to given the spatial distribution of patients.

The proportion of ethnic minority GPs by practice is defined in the catchment area model in the previous section, where the patient registration length is also taken owing to its significance in those models. This constitutes an addition to the model in Lewis and Longley (in press). So that the models presented in Lewis and Longley (in press) could be represented within a multilevel framework, the patients were not selected as in Lewis and Longley by whether they were within the Borough boundary of Southwark, but rather by whether or not their nearest GP surgery was a Southwark GP surgery. This was because the requisite information to allow an effective multi-level model was not available in the dataset of GP surgeries outside of Southwark. This means that the number of observations in each dataset are slightly different from the original Lewis and Longley paper; the interpretation of results has also changed slightly from a comment about all people within Southwark, to all people for whom a Southwark GP surgery is their nearest surgery. As is evident in Table 7.6, however, this does not seem to significantly change the conclusions that can be drawn.

<i>Variable</i>	Model 1	Model 2	Model 3	Model 4
Dist near GP surgery (km or minutes)	-1.37*** (0.0189)	-0.115*** (0.00158)	-0.00128*** (0.0000161)	-0.00178*** (0.0000211)
No. Local Surgeries	-0.135*** (0.00151)	-0.159*** (0.00160)	-0.147*** (0.00147)	-0.113*** (0.00142)
No. GPs	0.130*** (0.00167)	0.144*** (0.00176)	0.0723*** (0.00167)	0.0899*** (0.00166)
% minority GPs	-0.00393*** (0.000207)	-0.00206*** (0.000215)	-0.00909*** (0.000217)	-0.00601*** (0.000214)
Reg. Length	-0.0445*** (0.00262)	-0.0502*** (0.00274)	-0.0391*** (0.00255)	-0.0365*** (0.00253)
Patient Sex (Female)	0.00359 (0.00883)	0.00658 (0.00902)	0.0193** (0.00858)	0.0240** (0.00849)
<i>Age of Patient</i>				
16-24	-0.222*** (0.0191)	-0.182*** (0.0195)	-0.130*** (0.0185)	-0.122*** (0.0183)
35-44	-0.108*** (0.0172)	-0.106*** (0.0176)	-0.0626*** (0.0167)	-0.0490** (0.0165)
45-54	-0.338*** (0.0197)	-0.335*** (0.0202)	-0.253*** (0.0190)	-0.206*** (0.0188)
55-64	-0.413*** (0.0247)	-0.387*** (0.0252)	-0.356*** (0.0236)	-0.279*** (0.0234)
65-74	-0.455*** (0.0230)	-0.443*** (0.0307)	-0.377*** (0.0288)	-0.312*** (0.0283)
75+	-0.530*** (0.0321)	-0.466*** (0.0328)	-0.481*** (0.0311)	-0.321*** (0.0306)
<i>Interaction between Patient Age and Patient's Length of Registration with their GP surgery in Years.</i>				
16-24 Interaction	0.0206*** (0.00360)	0.0258*** (0.00373)	0.0117*** (0.00351)	0.0171*** (0.00347)
35-44 Interaction	0.0131*** (0.00344)	0.0187*** (0.00358)	0.00649 (0.00336)	0.00873** (0.00332)
45-54 Interaction	0.0304*** (0.00333)	0.0390*** (0.00345)	0.0221*** (0.00324)	0.0214*** (0.00321)
55-64 Interaction	0.0359*** (0.00365)	0.0417*** (0.00379)	0.0275*** (0.00355)	0.0248*** (0.00352)
65-74 Interaction	0.0343*** (0.00406)	0.0439*** (0.00416)	0.0234*** (0.00396)	0.0227*** (0.00390)
75+ Interaction	0.0475*** (0.00396)	0.0549*** (0.00407)	0.0366*** (0.00387)	0.0304*** (0.00385)
(base category for age is 25 – 34 years old)				
<i>Ethnicity of Patient</i>				
African	-0.608*** (0.0332)	-0.476*** (0.0342)	-0.605*** (0.0330)	-0.709*** (0.0329)
East Asian	-0.122** (0.0465)	-0.0627 (0.0472)	-0.120** (0.0450)	-0.185*** (0.0446)
Eastern European	-0.0796 (0.0567)	-0.102 (0.0566)	-0.198*** (0.0555)	-0.172** (0.0553)
European	-0.0191 (0.0251)	0.00750 (0.0253)	-0.0550* (0.0246)	-0.0663** (0.0244)
Hispanic	-0.215*** (0.0467)	-0.159*** (0.0471)	-0.203*** (0.0459)	-0.308*** (0.0456)
Muslim	-0.306*** (0.0330)	-0.246*** (0.0334)	-0.366*** (0.0322)	-0.385*** (0.0321)
South Asian	-0.0509	0.0141	-0.220***	-0.223***

	(0.0609)	(0.0616)	(0.0578)	(0.0583)
Other/Unclassified	-0.100*	-0.0416	-0.193***	-0.199***
	(0.0461)	(0.0467)	(0.0449)	(0.0448)
<i>Interaction between Patient Ethnicity and Percentage of Minority GPs at Nearest Surgery</i>				
African Interaction	0.0102***	0.00864***	0.00914***	0.0114***
	(0.000507)	(0.000521)	(0.000527)	(0.000524)
East Asian Int.	0.00296***	0.00284***	0.00204*	0.00512***
	(0.000796)	(0.000792)	(0.000802)	(0.000777)
Eastern European I.	0.00370***	0.00377***	0.00465***	0.00437***
	(0.000887)	(0.000908)	(0.000921)	(0.000915)
European Int.	0.00141***	0.000648	0.00178***	0.00172***
	(0.000405)	(0.000415)	(0.000418)	(0.000415)
Hispanic Interaction	0.00544***	0.00362***	0.00497***	0.00629***
	(0.000736)	(0.000754)	(0.000759)	(0.000753)
Muslim Interaction	0.00510***	0.00499***	0.00556***	0.00635***
	(0.000520)	(0.000530)	(0.000534)	(0.000531)
South Asian int.	0.00290**	0.00119	0.00447***	0.00472***
	(0.00101)	(0.00103)	(0.00102)	(0.00102)
Other Interaction.	0.00325***	0.00177*	0.00416***	0.00415***
	(0.000729)	(0.000747)	(0.000750)	(0.000745)
(base category for ethnicity is British)				
Constant	0.788***	0.757***	1.37***	1.04***
	(0.0232)	(0.0244)	(0.0230)	(0.0226)
<hr/>				
	Log likelihood =	Log likelihood =	Log likelihood =	Log likelihood =
	-150064.16	-145612.59	-158567.8	-161290.83
	LR chi2(34) =	LR chi2(34) =	LR chi2(34) =	LR chi2(34) =
	25769.95***	29944.24***	26155.67***	21116.29***
	No. Obs. =	No. Obs. =	No. Obs. =	No. Obs. =
	242222	244362	253909	253968

Table 7.6: 4 Logit models based on Lewis and Longley (in press). Models 1 and 2 are distance/travel time unconstrained, whereas 3 and 4 are distance/travel time constrained by GP surgery capacity. Significance: * p<0.05, ** p<0.01, * p<0.001**

The logit model tested in Table 7.6, for all four models, is given by equation 7.6 below.

$$\begin{aligned}
 & \ln \left[\frac{\text{probability uses nearest GP Surgery}}{\text{probability does not use nearest GP Surgery}} \right] \\
 & = \beta_0 + \beta_1 \text{Distance to Nearest GP Surgery} \\
 & + \beta_2 \text{No. Local GP Surgeries} + \beta_3 \text{No. Doctors at Nearest Surgery} + \beta_4 \text{Patient Sex} \\
 & + \beta_5 \text{Years of Registration} + \beta_6 \text{Patient Age} + \beta_7 \text{Patient Age} * \text{Years of Registration} \\
 & + \beta_8 \text{Patient Ethnicity} + \beta_9 \text{Proportion of Ethnic Minority GPs at Nearest Surgery} \\
 & + \beta_{10} \text{Patient Ethnicity} * \text{Prop. Ethnic Minority GPs at Nearest Surgery} \quad (7.6)
 \end{aligned}$$

As per Lewis and Longley (in press) patients under the age of 16 are omitted from the model as their registration behaviour is largely constrained by those of their parents.

All four logit models are consistent with the results reported by Lewis and Longley (in press) in terms of headline outcomes. The closer (either by distance or travel time) a patient is to their nearest GP surgery, either with a constrained or unconstrained capacity, the more likely that patient is to use their nearest GP surgery. This has already largely been discussed in Chapter 5, with Figure 5.6 a useful spatial representation of this phenomenon. Further, when there are a greater number of local alternative GP surgeries, patients are less likely to use their nearest GP surgery, this may reflect the suggestion in Chapter 5 that patients are willing, given service density, to make small accessibility-based tradeoffs in distance or travel time in order to use a preferential GP surgery. Similarly, as the size of the nearest GP surgery increases – in terms of number of GPs – the likelihood of a patient using it increases. This may reflect a preference amongst patients for larger health centres.

The first apparent inconsistency in the results is the significance of patient sex: in the Lewis and Longley paper, and in both the unconstrained models shown in Table 7.6, sex is not a significant explanatory variable for patients using their nearest GP surgery. However, when the constrained models are reviewed, patient sex is notable for its significance at the 1% level. Whilst, there is evidence to suggest that patient sex may have an impact upon patient choice of GP surgery, it is usually observed at an interpersonal level between patients and individual GPs, rather than at the aggregate surgery level. This is because most GP surgeries in Southwark offer GPs of both sexes, and there is a relatively an even distribution of men and women across the Borough. In principle this calls into question the validity of using a constrained model (in which allocation of patients to their nearest GP surgery is subject to the size of the patient list at each surgery) in assessing access to GP surgeries. Further, at the time that the data were extracted there were no closed GP surgery lists in Southwark, so imposing a capacity might be seen as somewhat arbitrary. Similarly, patients will base their understandings of distance to their nearest GP surgery on personal circumstances, expressed in objective terms by the unconstrained models (Hawthorne and Kwan (2011) suggest that a subjective distance metric may include notions of quality effectively distancing more local services in terms of patients' preferences). What the constrained models may be doing, however, is representing a hidden dimension of service availability, subject to the capacities and tensions inherent in the physical and social environment of Southwark. Regardless, the use of unconstrained vs. constrained representations of a patients "nearest" GP surgery seems relevant to Harvey's (1973) sentiment that one cannot optimise the city.

The effect of patient age is consistent across all models: all patients are significantly less likely to use their nearest GP than patients within the 25-35 year old age band. The interaction effect with registration age is interesting however, whilst on its own it is suggested that increased years of registration lead to a decreased likelihood of using the nearest GP surgery, which is consistent with the discussion of GP surgery-defined catchment areas in the previous section; the interaction between age and years of registration suggests that all age groups are more likely to use their nearest GP surgery relative to the 25-35 group as the age of registration with their GP surgery increases. It is not clear why this should be the case.

The effect of patient ethnicity is somewhat varied across the models, although the effects upon Muslim and African patients highlighted in Lewis and Longley (in press) are consistent: African and Muslim patients are significantly less likely than British patients to use their nearest GP surgery, but are more likely to do so if their nearest GP surgery has a high proportion of ethnic minority GPs. It was therefore suggested that this is evidence of patient preferences for GPs that are ethnically similar to themselves: in Chapter 6 it is also suggested that language may play a role in this. This is a finding that can be validated anecdotally with relative ease, but it is novel in empirical terms, and offers a useful insight into the operation of a system of healthcare in an inner city context. The significance of other groups varies across the 4 models, when subject to constrained capacities South Asian, European and Eastern European groups are rendered statistically significantly less likely to use their nearest GP surgery than British patients, whereas assuming unconstrained capacities there is no statistically significant difference. However, there is no inconsistency across models in the interaction term which suggests that patients from all other ethnic groups are increasingly likely, relative to British patients, to use their nearest GP surgery as the minority ethnic mix of that GP surgery increases.

A multi-level model was specified to test the unconstrained models (1 and 2), owing to the uncertainty of the meaning of specifying a GP capacity constrained model. Models 3 and 4 were not replicated in a multi-level format. The patients were nested within their nearest GP surgeries, and random effects were introduced for the proportion of minority ethnicity GPs at the nearest surgery, making it possible to introduce a cross-level interaction between GP ethnicity and patient ethnicity. Similar limitations as discussed in the previous section were experienced, and again repeated models were unable to be run due to non-concave optimisation. The log-likelihood function of a model can be considered non-concave if the

	Model 1		Model 2	
<i>Variable</i>	Coefficient	Std. Error	Coefficient	Std. Error
Dist near GP surgery (km or minutes)	-0.00177***	0.0000209	-0.150***	0.00179
No. Local Surgeries	-0.0901***	0.00234	-0.0801***	0.00255
Patient Sex (Female)	0.00685	0.00903	0.00151	0.00933
Years of Registration with GP Surgery	-0.0448***	0.00268	-0.052***	0.00283
% minority GPs	-0.0108**	0.00340	-0.00597	0.00657
<i>Age of Patient</i>				
16 – 24	-0.227***	0.0195	-0.198***	0.0202
25 – 34	-0.108***	0.0176	-0.111***	0.0182
35 – 44	-0.351***	0.0201	-0.364***	0.0208
45 – 54	-0.423***	0.0252	-0.411***	0.0261
55 – 64	-0.469***	0.0306	-0.473***	0.0317
65 – 74	-0.526	0.0329	-0.475***	0.0340
<i>Interaction between patient age and years of registration with GP surgery.</i>				
16 – 24 Interaction	0.0189***	0.00368	0.0253***	0.00384
25 – 34 Interaction	0.0130***	0.00351	0.0187***	0.00368
35 – 44 Interaction	0.0300***	0.00341	0.0400***	0.00355
45 – 54 Interaction	0.0369***	0.00373	0.0443***	0.00389
55 – 64 Interaction	0.0358***	0.00413	0.0464***	0.00426
65 – 74 Interaction	0.0478***	0.00404	0.0562***	0.00417
(base category for age is 75 + years old)				
<i>Ethnicity of Patient</i>				
African	-0.338***	0.0348	-0.347***	0.0362
East Asian	-0.110*	0.0488	-0.0845*	0.0504
Eastern European	-0.0412	0.0594	-0.0475	0.0608
European	-0.00243	0.0264	0.0158	0.0271
Hispanic	-0.0639	0.0490	-0.0490	0.0502
Muslim	-0.176***	0.0348	-0.204***	0.0357
South Asian	-0.210***	0.0631	-0.123*	0.0646
Other or Unclassified	-0.0408	0.0484	-0.00236	0.0500
<i>Interaction between Patient Ethnicity and Percentage of Minority GPs at Nearest Surgery</i>				
African Interaction	0.00611***	0.000528	0.00736***	0.000552
East Asian Int.	0.00310***	0.000819	0.00383***	0.000839
Eastern European I.	0.00319***	0.000922	0.00345***	0.000967
European Int.	0.00126**	0.000421	0.00101*	0.000441
Hispanic Interaction	0.00343***	0.000764	0.00318***	0.000797
Muslim Interaction	0.00340***	0.000542	0.00504***	0.000562
South Asian int.	0.00566***	0.00105	0.00345***	0.00108
Other Interaction.	0.00253***	0.000756	0.00204**	0.000792
(base category for ethnicity is British)				
Constant	1.79***	0.222	1.26*	0.431
<i>Random-Effects</i>				
Variance(% Min. GPs)	0.000218	0.000108		
Variance(cons)	1.04	0.387	1.98	0.482
Cov(% Min. GPs, Cons)	-0.0139	0.00652		
No.of Obs = 242222	Log likelihood = -145218.18		Log likelihood = -137359.07	
No. of Groups = 41	LR test vs. logistic regression:		LR test vs. logistic regression:	
Obs/Group min,avg,max	chibar2(03) = 15882.02 (0.000)		chibar2(01) = 23338.16 (0.000)	
1630, 5907.9, 14557				

Table 7.7: Multi-level mixed effects based upon models 1 and 2 in Table 7.6.

function has many ridges, saddle points, and flat areas (Steenbergen, 2003) this means that Stata cannot establish a new set of parameter estimates based on that particular iteration of the maximum-likelihood optimisation procedure which minimises the value of negative log-likelihood for the model. In some circumstances different optimization procedures can be used to effectively minimize the log-likelihood function of a model, however in others it can prove impossible. Experimenting with the variables included will usually allow for the exclusion of problematic variables; for this reason the GP surgery level variable pertaining to the number of GPs at each surgery had to be dropped from the model. The results are tabulated in Table 7.7 on the previous page.

Again, the multi-level formulation tells a very similar story to that which is evident from the standard logit model. However, the complexity of the specified multi-level models is not as sophisticated as might be wished for, owing largely to the computational difficulties experienced – the addition of multiple random effects and the expectation of random slopes clearly pushes the available software (in this case Stata 10) beyond its capabilities, calling into question whether the technique is mature enough to handle the analysis of a dataset of this size. Indeed, it is clear that much of the variance in the random effects is currently unaccounted for. This may be largely because of acknowledged, and recurrent issues with computational optimisation procedures which by virtue of their approach do not scale well to larger problems, and are often only improved by developing faster CPU speeds in computer hardware, or by the recent trend for parallelisation of computational processes.

The difficulties faced in applying multilevel modeling in this chapter highlights the computational challenge in estimating such models. De Leeuw and Kreft (1995) state that particular algorithms can make a huge difference to obtaining modeled parameter estimates, but that factors such as computational speed are generally traded-off against the ability of alternative methods to reach an unbiased solution. This is reflected in the use of Laplacian Approximation, rather than the more computationally expensive Gaussian-Hermite Quadrature in this chapter. In practice, the more difficult problem faced in this analysis came from the difficulty of finding the solution which best minimizes the negative log-likelihood function of the model without the optimization process failing due to the non-concavity of the log-likelihood function. The log-likelihood function of a large problem is complex, and can often only be solved by iterative approximation of a near optimal solution, introducing “badly behaved” variables can add to the difficulty inherent in solving a problem and

deriving useful parameter estimates. Weise et al (2009) classify different types of functions in Figure 7.9, highlighting those that are difficult to optimise with question marks, and annotating those that lead to local, misleading minima. In principle an optimum solution can be found for all these functions, it simply requires that the entire set of possible values are considered; optimization routines such as those in Stata do employ special techniques for “stepping” across the surface of the function in order to enhance the likelihood of finding a solution, however this could conceivably take a very long time and there are still few guarantees that the solution arrived at is not simply a local minima. The general practice in such situations is to reduce the complexity of the function by specifying a simpler model by excluding the variable(s) that seem to most hinder the optimisation. Of course, this means being unable to estimate particular models, which leaves question marks over the significance of particular models with respect to understanding the research question at hand.

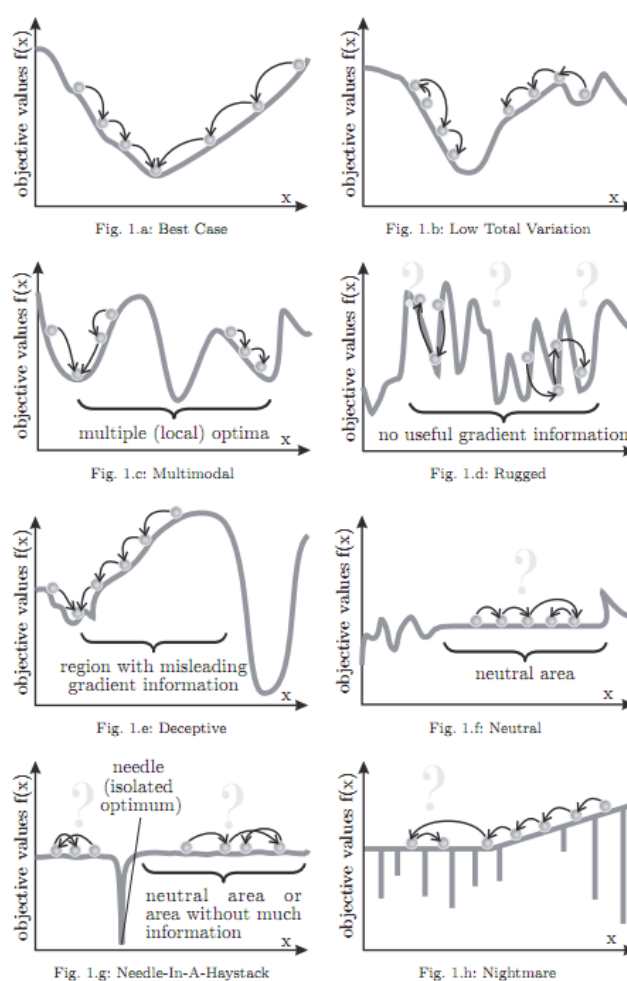


Fig. 1: Different possible properties of fitness landscapes (minimization).

Figure 7.9: Difficult functions to optimize effectively (Source: Weise et al, 2009 Fig.1 p. 4)

7.4 Consolidation

This chapter has tackled one of the major rhetorical aspects of recent NHS reform agendas – patient choice. Whilst it is easy to accept that “giving choice to individuals and groups who previously had none... will extend to all a privilege that was previously confined to those who could afford private healthcare” (Dixon and Le Grand, 2006:166), it is also clear that the equitable provision of healthcare services by the NHS is contingent on more than simply creating an artificial environment in which there is the potential for patients to choose.

An analysis of both the existing GP surgery catchment areas, as well as patient registration with their nearest GP surgery, demonstrates the association between factors such as the length of a patient’s registration with a GP surgery, and the additional significance of registering with an ethnic minority GP for ethnic minority patients. In Chapter 5 the complexity of patient registration with GP surgeries was demonstrated with respect to the observed distribution of patients, and it was suggested that the density of service provision allowed patients to consider making small accessibility-based tradeoffs in order to register with preferential GP surgeries. This chapter reinforces this observation, highlighting the importance of “competing destinations”, that is, the presence of local alternative surgeries understood in terms of the extent of their service areas (Chapter 6). Patients who have a greater choice in terms of number of local services are less likely to use their nearest GP surgery, suggesting that choice is highly contingent on opportunity due in a large part to the location-based nature of primary care service provision. This is particularly apparent for African and Muslim patients, but exists to a greater or lesser extent for all ethnic groups.

Lewis and Longley (in press) use an unconstrained approach to characterise access and registration with the nearest GP surgery, making it difficult to assess the extent to which observed differences between different population groups manifest the effect of constraints on the distribution of patients within the system, or the actively expressed preferences of patients. The use of the market areas developed in Chapter 5 is an attempt to account for the effects of these constraints within the model: however, as discussed it is unclear how the representation of these constraints would actually be conceptualized by patients in reality. Further, the expression of constraints as engineered in Chapter 5 is based on the condition of Pareto Optimality, meaning that the constrained distance and travel times are based on an equitable characterization of access for all patients, and yet we know that there is a good chance that health inequalities exist across different social and demographic groups.

Therefore, we cannot claim to have isolated the effects of preference using the constrained model of network distance and travel time: however, the fact that the constrained models complement the results of the unconstrained models is useful with regard to interpretation. Having said this, the significance of the patient sex under the constrained model is curious, and might be worth further study.

The analysis in this chapter posits the role of the GP surgery as a place that provides local services in a way that tries to serve the population as a whole (i.e. spatial equity). Further work understanding the characteristics of the different GP surgeries might reveal what is driving differential registration behaviours. This could assist in planning delivery of healthcare in the UK within the local community remit specified by the NHS, consistent with the mantra of improving patient choice. It is clear that patient choice, at least in Southwark, and perhaps, by extension, in other inner city urban areas, is an established practice amongst patients. At the present time patterns of registration are highly spatially contingent and it is unclear what, if any, effect a scaling back of the geographic regulation of access to primary care will do. Patterns of registration with GP surgeries in Southwark, highlighted both in this chapter and in the previous one, suggest that there are different patient compositions in different GP surgeries owing to patient and GP characteristics and local contexts. However, there is little to suggest that these patterns are inequitable. Whilst much of this arises from the lack of a rigorous assessment of GP surgery quality by the NHS, and the perceived homogeneity of service at any given GP surgery, the variation in care opportunities are changing more rapidly now than at any other point in the history of NHS primary care. As GP consortia are formalised (they are being piloted at the time of writing, with all Southwark GPs forming a single consortium exclusive of GPs outside the Borough), it will be important to capture changes from a recognized baseline of patient behaviour in order to assess the role of greater patient choice, and independence of primary healthcare suppliers from central government. The NHS needs to avoid any discernable polarisation in the provision of services and registration of patients so as to avoid claims of rising inequity. How people access services, and not just GP surgeries, is an important requirement towards understanding individual and community welfare.

In the next, and final, empirical chapter we shift scales, focusing on the hospitals in Greater London as a way of engaging further with the notion of patient choice and the purchaser-provider split in the NHS. This provides additional context for the Southwark region in terms

of the predisposition of patients towards choice in healthcare and highlights further changes to the NHS that proposed reform could bring about. In doing this, a health informatics approach is employed which highlights the increasing value of spatial health data.

8. Operationalising Health Data for Hospital Trusts

8.1 Introduction

The previous chapters have focussed on the role of primary care in the NHS, using a case study of Southwark to explore patient registration behaviours with GP surgeries. Evidence for patient registration behaviours was uncovered using a number of spatial analytical approaches to thinking about local access to, and registration with, primary healthcare, moving from the normative definition of an accessibility-based allocation of patients, to charting the *de facto* service area from the observed distribution of patients by GP surgery. In Chapter 7, the context of a changing NHS was introduced in the light of proposed reforms set out in a white paper, and in the process of being carried into law by the health and social care bill. Investigating patient registration behaviour allows an insight into the current situation that is highly relevant to a patient choice agenda, and seeking the abolition of perceived constraints to choice such as GP surgery catchment areas. Taking a broader view, the changes to the NHS were also characterised in terms of an increasingly primary care focussed approach, owing in part to cost savings, but also as a result of a changing healthcare agenda from a reactionary curative approach (Johnstone and McConnan, 1995), to an interventionist health-improvement perspective (Greener and Powell, 2008) which was seen as best operationalized as a market, taking advantage of local care and devolved decision making (Stevens, 2004; Moon and North, 2000).

However, proposed changes in the NHS are not specific to how patients access primary care, but apply more broadly to how care is provided at out- and inpatient levels as well. In the NHS a primary care GP is responsible for referring a patient from the general medical care setting to specialist care, usually within hospitals. As such, GPs were seen as gatekeepers to the specialist care system, an emergent phenomenon in recent years in countries with scarce medical resources (Forrest, 2003). However, Shaw (2005) emphasises the changing role of the GP in this process, from a defined “Doctor-Patient” relationship to a “Patient-Professional” dichotomy in which the patient takes precedence, giving the patient a new freedom and an increasing ability to choose. This was made most apparent recently through the previous government’s “choose and book” scheme allowing patient choice at referral as to the time, date and place of their first outpatient appointment and is reflected in

the NHS constitution (DH, 2010a). The revolution in patient –centred care, and the promotion of choice, has to some extent been driven by the furtherance of competition within the NHS, particularly marked by the increased role of primary care in purchasing care from secondary care hospital suppliers, which are mandated to become more independent, public facing, quasi-social enterprise bodies called “foundation trusts” (DH, 2005). However, as Kirkpatrick (2011) states “while competition may stimulate efficiency and innovation, there are no guarantees that market signals will lead to services that are responsive to the needs of patients” (p.1).

A central plank to the effective operation of viable hospital foundation trusts therefore, must be the beneficial usage of healthcare data; knowing how patients use specialist care is key to providing effective and relevant care choices that save money and improve quality of service for the patient, whilst maintaining the viability of economically-pressured NHS hospital trusts as they transition to foundation trusts. In this chapter, spatial patterns of use of inpatient and outpatient care in Greater London is considered in terms of the availability of local provision, and in light of the availability of choice, with focus on Greater London.

8.2 Competition in the NHS

Competition in the NHS has been apparent in varying forms in the NHS since 1991, albeit subject to the specific politics of the administration in charge of government (Propper et al, 2008). The intended consequence of its existence has always broadly been the improvement in quality of care for patients and, again, increasing patient choice, as reflected in the “Working for Patients” White Paper (DH, 1989). The 1991 reforms created an “internal market” within the NHS, decoupling purchasers (then District Health Authorities, and a small number of GP fundholders) from providers (NHS Trusts- a hospital or group of hospitals), and required the purchasers, who were given budgetary control, to buy care from providers. Crucially, the NHS Trusts now no longer received an annual income from central government, but by way of contracts agreed with purchasers which were subject to competitive effects from other providers. Frosini et al (2011) suggest that the market itself was defined by geographical proximity – there was little value to purchasers having contracts with non-local services, indeed patients and GPs “appeared to be loyal to local providers (p.1) – and competition was mainly on the periphery of a provider’s market area, where other “local” providers were viable alternatives for patients. Moreover, competition

was often not possible due to geography (Propper et al, 2008), or the fact that local markets did not overlap owing to the types of service offered. Furthermore, the emergent ability of purchasers (GPs) to deliver traditionally hospital-based services meant that competition was not strictly between hospitals (NHS Trusts), rather, it was between purchaser and provider (Frosini et al, 2011).

Various systemic distortions in how the purchaser-provider relationships operated, including the difference between GP fundholders buying services, as opposed to district health authorities, and the varying forms of providers (health-authority hospitals, NHS Trusts, private companies etc.) led to the allegation that the NHS was not upholding its duty of equity of healthcare for all, and to the subsequent reforms by the Labour government from 1997 (Brereton and Vasoodaven, 2010). The competition reforms of 1991 were largely abolished by Labour upon their rise to power in 1997. However the broad impetus of the 1991 reforms, which devolved purchasing and provision of health care from a central government function, to one that was more locally based, was subsequently carried over in the 2002 reforms of the Labour party. The 2002 reforms, which focussed less on competition per se (Mays, 2011), saw the creation of Primary Care Trusts (PCTs), performing a similar role to the (district) health authorities that they replaced, however the value of local service was further exemplified by the introduction of 151 PCTs from 100 district health authorities (although these numbers varied over time from 1991-1997 and from 2002 onwards owing to various NHS rationalisations). PCTs control a huge amount of the NHS budget (c. 80%) and are tasked with both purchasing care, and also overseeing that care effectively meets community needs. In line with the new PCTs, GP fundholding was reinvented as practice-based commissioning, but with a more pronounced focus on community care, rather than hospital-based care provisioning (Brereton and Vasoodaven, 2010). On the side of providers, the revisionist Labour NHS introduced the Foundation Trust which allowed NHS hospital trusts to become more independent in the context of the NHS system, again focussing on community decision making, rather than centralised policy. However, integral to the 2002 reforms was an all-encompassing reliance on performance measures as a surrogate for quality and efficiency, which is where proposed Conservative-Liberal NHS reform derives a portion of its criticism of Labour policy (DH, 2010b).

Whether or not increased competition drove improvements in quality of care is debated, however Propper et al (2008) suggest that an unfortunate driver of competition was

uncertainty, which derived from a sudden dependence of hospitals on contracts secured from purchasers. This was reflected in the changing distribution of patient flows to hospital care, but according to Propper et al (2008) did not necessarily accord with increased, or indeed any, competition between hospitals. It was argued that the effect of uncertainty and changes to patterns of service delivery meant a general failure in long-term strategic planning, which was exacerbated by a lack of data on outcomes which could be used to justify quality and cost of service to prospective purchasers. It was because of these concerns that, post-1997, overt competitive aspirations were transformed to stress cooperation in health services planning (Le Grand, 1999). The role of cooperation is evident in Frosini et al (2011) who note the "embeddedness of social and institutional relationships" (p.4) in driving forward cooperative rather than competitive associations between purchaser and provider.

Dixon et al (2010) suggest that the effect of competition on patient choice was actually relatively limited, and systems put in place to provide a freer choice usually resulted in patients using local providers anyway. They suggest that there might be some equity concerns though, noting that older patients, and patients educated to degree level were more likely to use non-local services, whilst there was a sense amongst GPs that non-native English speakers were being overlooked. Despite this, they found that by and large patients based their decision making on their experiences, those of their GP, and family and friends in preference to the available information in pamphlets or online through services such as NHS Choices. Dixon et al (2010) suggest that for competition in the NHS to be effective, patients need to favour the high-performing Hospitals and other service providers, but that traditional geographies of service provision largely endure, undermining this requirement. Brereton and Vasoodaven (2010) suggest that competition in the NHS has failed to materialise along the lines of classical economic theory, and that this constitutes a failure because the extra costs of competition have failed to bring tangible benefits. Going further, Propper et al (2008) suggest that competition between 1991 and 1997 had actually reduced quality in terms of measures of quality that were unobservable at the time such as mortality rates for specific diagnoses or procedures, whilst simultaneously increasing quality in terms of lowering the headline grabbing "waiting time" measure.

The reforms proposed in the "equity and excellence" white paper attempt to deal with a number of the misgivings of previous competition-focused policies, whilst simultaneously reinforcing community-based care and devolution of services. However, there is little to

support these actions either in terms of the effectiveness of market reform, or the effective involvement of communities in managing their healthcare in a more democratic way (Asthana, 2010). Aside from the primary care agenda of creating purchasers which are consortia of GP surgeries discussed in the previous chapter, it is expected that by 2014 all NHS providers become Foundation Trusts, who will again compete, not only with each other, but with private and voluntary sector providers as well. A regulatory body – Monitor – will be established to oversee this, and the ability of central government to intervene will, to a significant degree, be distanced by the creation of an NHS Commissioning board. This is also reflected in the abolition of not just PCTs, but also Strategic Health Authorities (SHAs) and a number of other bodies. Creating buy in amongst health professionals to the proposed reforms has been difficult so far for the present government (Walshe, 2010), with suggestions that there is little evidence that NHS performance is structurally based, worsened by the belief that large transitional costs of reorganisation and the impact of reorganisation itself will have profoundly negative effects on service performance.

8.3 Managing Competition through Spatial Health Informatics

Information is a cornerstone of the proposed changes to the NHS, and the concept of spatial data infrastructure has been discussed in this regard in Chapter 2. Whilst information, it is asserted, will help patients make more informed decisions both in regard to their own care, and to care in their communities, there is also a strong requirement for providers to be as well informed as possible. Success or failure of Foundation Trusts in a competitive environment could hinge upon their ability to identify local gaps in purchasing, as well as to target improvements in quality through outcomes and performance monitoring. Advances in social marketing and consumer health informatics (Eysenbach, 2000) are becoming integral to reducing costs and driving efficient and effective health interventions, leaving users of these systems much better positioned within the healthcare marketplace. It is clear from the discussion in the previous section that geography, and particularly a sense of “locality” of service has an enduring role to play in the pattern of healthcare provision, and as a consequence Hospital Trusts will need to develop the requisite spatial techniques to compete effectively. The continued focus on communities and the breaking up of the now

accepted geographies of care at PCT, and SHA levels will mean an increasing requirement for health data that is routinely available at sufficiently small levels of areal aggregation.

Further, in order to be competitive, and (it is hoped) to drive up standards, every foundation trust will need to understand the performance of its competitors. This will necessitate an understanding first and foremost of local demography, one that is not reliant on the decennial censuses, but operationalises existing data that: are more temporally relevant, as demonstrated in Chapter 4; uses midyear estimates; or (if plausible) small area estimates from sample surveys or spatial micro-simulation approaches. On top of this, the changing context of the local environment is important, be it regeneration of housing stock, transport infrastructure or accessibility characteristics of public transport. In Southwark, a small number of records (low hundreds) were excluded from the patient register data during the data augmentation process described in Chapter 2 owing to the fact that the recorded addresses were for social housing estates that had been demolished by the council some 4 years previously. In a neoliberal sense, better information at the foundation trust will allow them to make a better account of themselves to their public members, aiding transparency and avoiding the inevitability that cutting costs is necessarily detrimental to the social justice of a healthcare system.

Using Hospital Episode Statistics for 2003/04 to 2008/09, which capture a period of regrowth of the patient choice agenda in the NHS under a Labour government, and a maxim of cooperation not competition, exploratory spatial data analyses are conducted to investigate the extent to which competition is evident in Greater London. It does this by looking at the three different sites of patient involvement with the care system – the patient's home neighbourhood, the patient's GP surgery, and the provider of in- or outpatient care, usually an NHS Trust Hospital. Each level has its own geography, and each is a potential site of choice for the patient, thus each level is of fundamental importance to understanding the system of healthcare in Greater London.

8.4 Characterising Utilisation of Hospitals in Greater London

Greater London (henceforth simply referred to as London) is an important context for health and healthcare within England (the scope of the devolved NHS England); the sheer size of London as a continuously urban phenomenon, and the associated high population density,

and large overall population, coupled with its financial and service sector importance to the knowledge economy puts it squarely in the “world city” category. Further, it is home to an extremely diverse population regardless of the dimension by which this is assessed, which presents challenges to providing effective healthcare that are without comparator outside of the London context. The history, and remarkable poly-centricity, of London has led to the existence of a unique healthcare infrastructure, and seen it at the forefront of structured management reforms and leadership through NHS London, the strategic health authority responsible for London.

London consists of 32 boroughs, with the City of London generally excluded owing to unique status of the Corporation of London, although it is included in this analysis.

8.4.1 An Overview of Patient Usage of Healthcare in London

Patient data are extracted, by year, for all admissions to inpatient and outpatient care for the set of 4,765 LSOAs (Lower Super Output Areas) which define London. A LSOA is the second smallest areal census dissemination geography after Output Areas (OAs) and includes around 1,500 people on average. For any year, in terms of either inpatient or outpatient care, around 99% of care is provided by NHS Trusts, or NHS Trust treatment centres which were designed to provide extra clinical capacity. Treatment centres are dedicated units devoted to short term elective surgeries and diagnostic procedures operated by some NHS Trusts in order to cut waiting lists, and provide consistency to hospital procedures which might otherwise be influenced by the unexpected requirement for emergency surgeries (DH, 2008b). Despite this, over the period from 2003/04 to 2008/09, independent providers went from providing no care, to providing care for c. 17,000 patients in 07/08 and 08/09. Whilst this is a tiny fraction of a percent of all admissions in London, it seems to be growing during this period, and is likely to grow further subject to NHS reforms.

<i>Year</i>	03/04	04/05	05/06	06/07	07/08	08/09
Inpatient Admissions	1,751,692	1,836,717	2,009,177	2,169,219	2,189,341	2,291,117
Unique Inpatients	936,439 (1.87)	947,132 (1.94)	1,005,055 (2.0)	1,062,944 (2.04)	1,053,566 (2.08)	1,083,119 (2.12)
Outpatient Admissions	9,113,430	9,942,292	10,868,224	11,335,437	11,505,237	12,889,002
Unique Outpatients	2,385,414 (3.82)	2,555,619 (3.89)	2,679,146 (4.10)	2,687,202 (4.22)	2,666,439 (4.31)	2,786,252 (4.63)

Table 8.1: Number of admissions and number of unique patients to inpatient and outpatient care in London by year (admissions per patient).

Table 8.1 suggests that both inpatient and outpatient admissions in London have risen over the time period, both in terms of the absolute number of admissions, and the number of patients treated. In addition, the number of admissions per patient has risen in both cases, suggesting an increasing burden of care for the health services in London. Figure 8.1 demonstrates how these overall rates actually break down by patient admissions annually; only the mean for all 6 time periods is reported due to the near complete correlation in percentage values across years. What is clear from Fig 8.1 is that inpatient and outpatient admissions are distinctly different, whilst the majority of outpatients are required to make more than one annual visit to hospital (although this finding is subject to the arbitrary start and end dates accounting for the period of a year in the HES data), the opposite is true for inpatients. On this basis, inpatient and outpatient data ought to be treated separately as patient decisions for care may vary by the requirement to make multiple trips, indeed, even within the broad inpatient and outpatient categories, patients who are aware of the potential for multiple visits may choose to use more local services, or may use different services depending upon their specific circumstances.

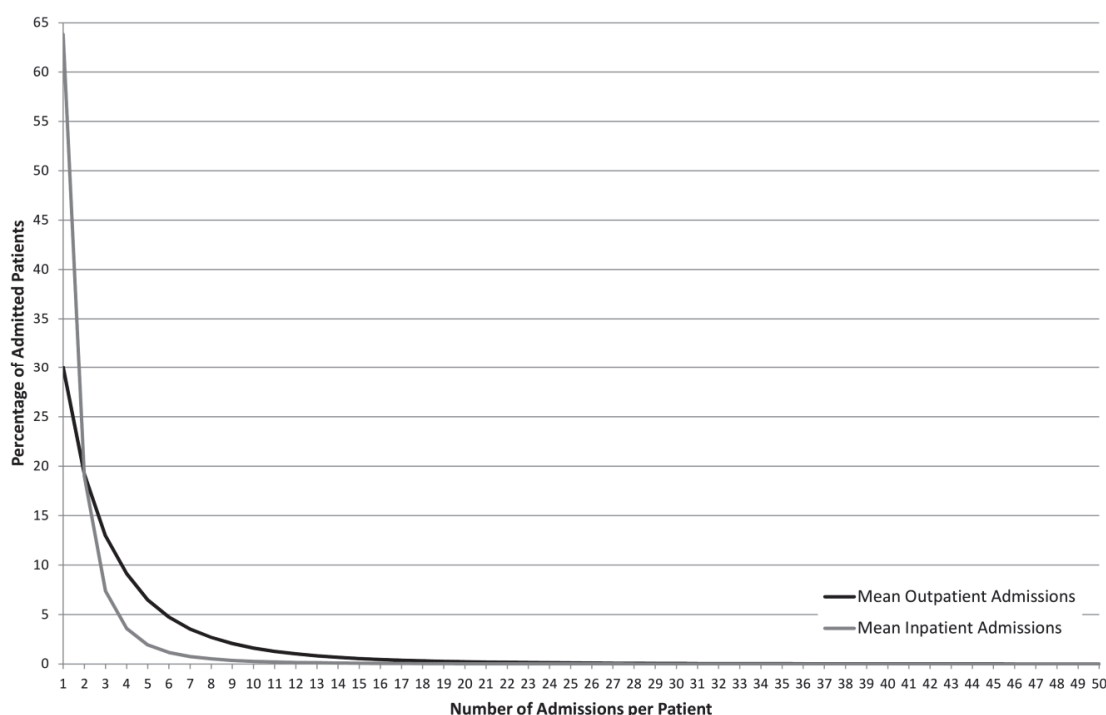


Figure 8.1: Mean percentage of inpatients and outpatients admissions in London by number of annual visits.

Patients recording more than 1 inpatient or outpatient attendance annually may attend different hospitals, or healthcare providers for each attendance; Figure 8.2 demonstrates the percentages of outpatients (8.2A) and inpatients (8.2B) for increasing frequency of annual

attendance using multiple providers. Values are aggregated across all years in order to account for small numbers of patients attending multiple times (as demonstrated in Figure 8.1), particularly in the inpatient data. This may arise because of the similarity of the relationships across time periods. Again it is clear that there are distinct differences between patient attendances for inpatient or outpatient care: outpatients attending multiple times in

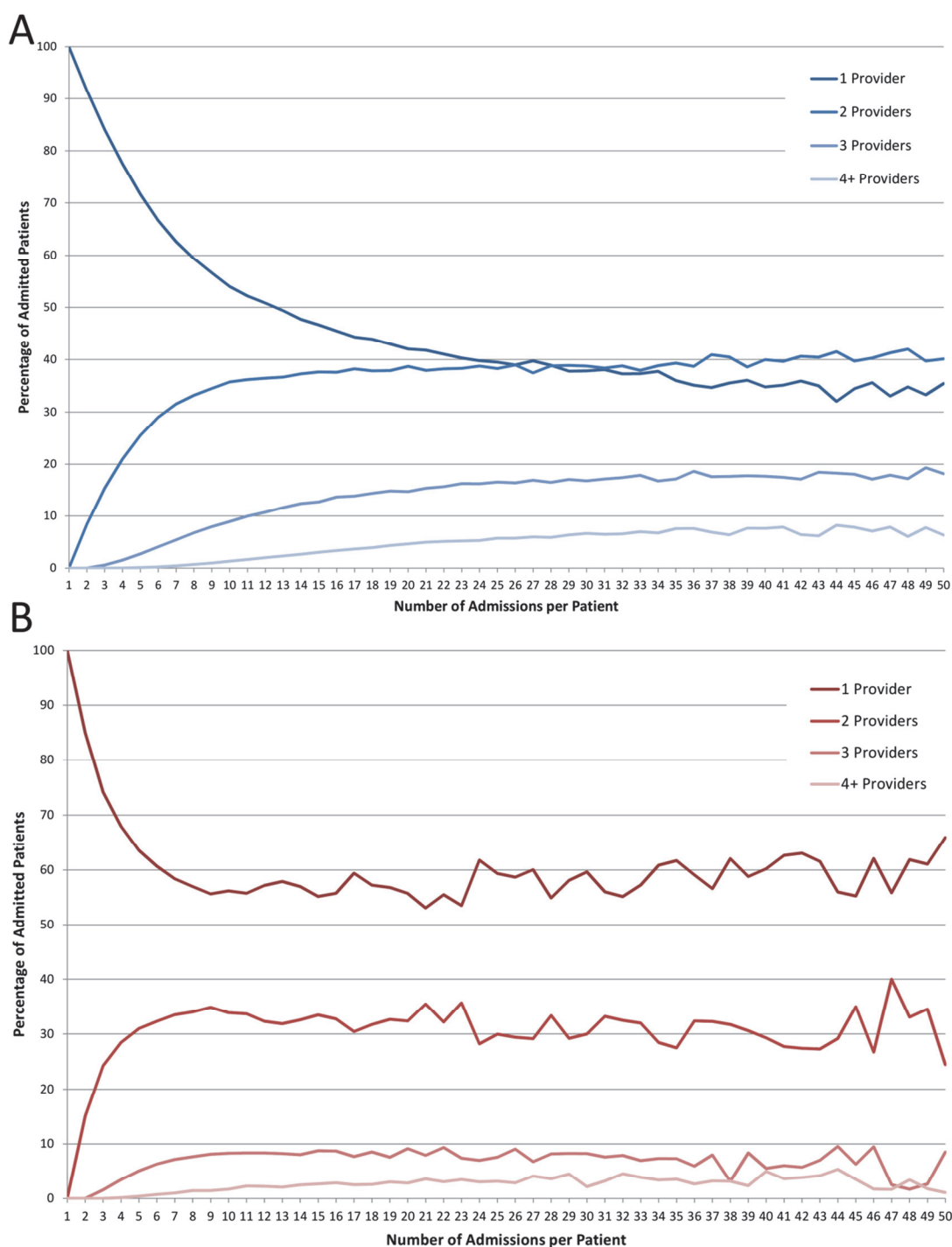


Figure 8.2: Mean percentage of outpatients (A) and inpatients (B) admissions in London by number of annual visits and number of different providers used per patient.

a year are less likely to use a single care provider as individual attendances increase, until such a point as patients are more likely to have attended 2 different providers than a single provider. This is not the case for inpatients who, regardless of number of attendances, are consistently more likely to use a single provider. This most likely reflects the different implications of attending a hospital for, for instance, a consultant visit following a GP referral, or a one-day elective surgery, as opposed to inpatient care which could see a lengthy spell of hospitalisation.

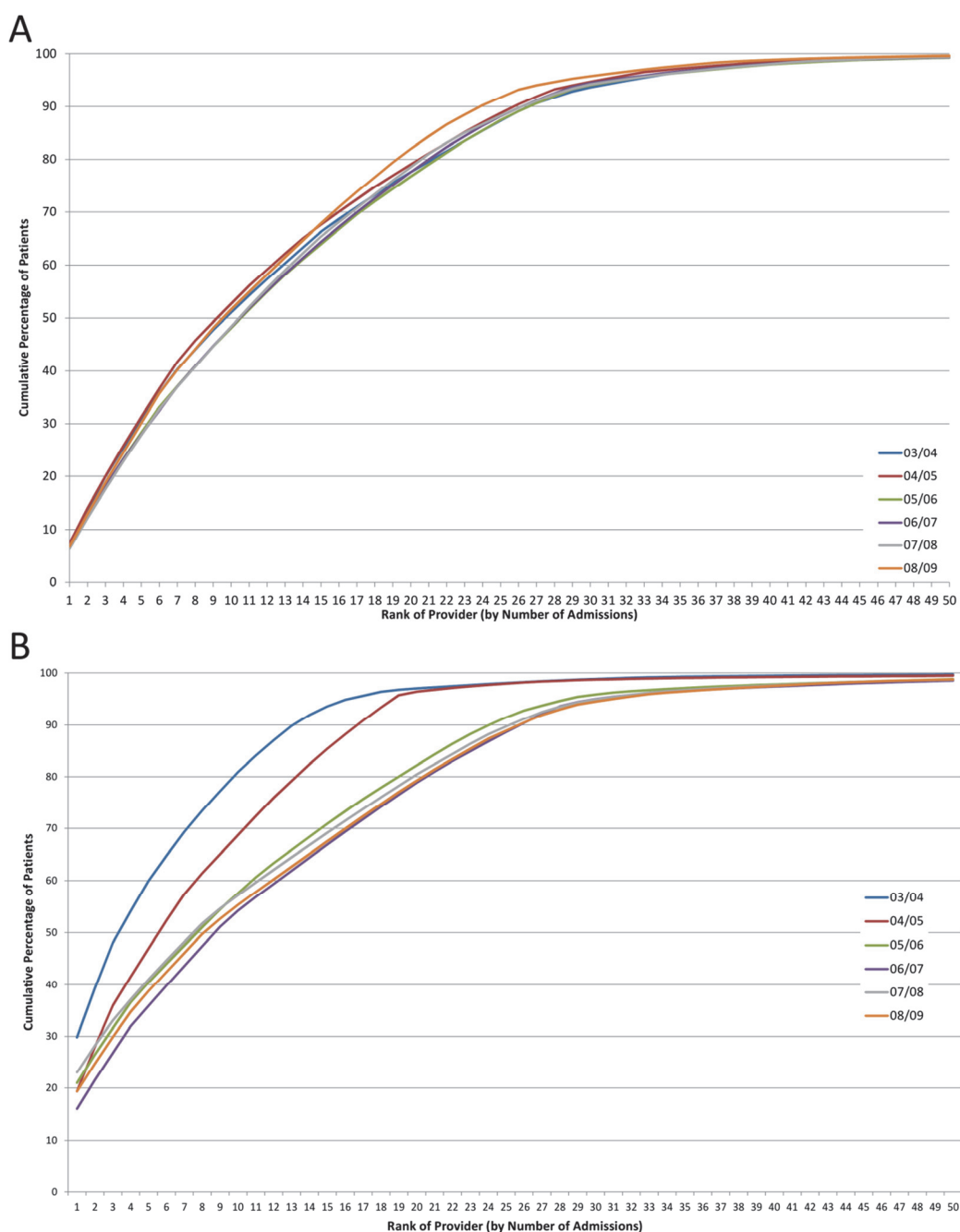


Figure 8.3: Cumulative Percentage of outpatients (A) and inpatients (B) served by different providers, ranked by number of admissions per provider (where rank 1 = most admissions).

Whilst, NHS London (2011) currently reports providers that include 20 NHS Acute trusts, and 16 Foundation trusts, the actual recorded numbers of providers for London residents is actually considerably higher, accounting for the myriad possible suppliers both within London, and in fact across England – owing to care received in hospitals outside for particular specialisms, or simply due to patient circumstances at the time, being on holiday and requiring routine care, for instance, or being admitted to hospital via Accident and Emergency. Figure 8.3 demonstrates the usage of different providers by London patients, showing that a relatively small number of sites are responsible for the majority of patient care.

The two graphs in Figure 8.3 are actually cut off at rank 50 for clarity – in fact the distribution of providers by rank of their admissions is long-tailed, with a large number of suppliers providing care to only a few patients. Whilst Figure 8.3A shows a general annual consistency, 8.3B shows 2 years for inpatients (03/04 and 04/05) which are markedly different from the general trend of the other years, this seems to be due to the densification of potential suppliers, both in terms of the introduction of NHS Trust treatment centres, which are recorded separately to the Trusts themselves, as well as the emergence (albeit limited) of independent suppliers in the system. This effect seems to be independent of the previously computed Figures 8.1 and 8.2 in that it does not seem to have led to an effect on patient admission choices.

The final general “global” (i.e. non-spatial) enquiry based on London data is the identifier of the patient’s registered GP surgery. This is the weak spot in the data when it is derived by the patient geography – as the selection is by LSOA code for London, we will always have a full record of patients by LSOA of residence, and of the provider of their healthcare because the data is all hospital episodes-based, however we may not have a full record of the patients GP surgery. The GP surgery record allows for the passing on of any results, allowing for community care of medical conditions where required, however it is not always an indicator of the referring party, as patients can be referred by NHS Walk-in centres, through accident and emergency, or by other hospital consultants. There are several situations in which the GP surgery reference may not be known however, and the NHS has codes for these: V81999 indicates that it is known that a patient is registered with a GP surgery, but it is not known which, this can be the case if the patient is unconscious or uncommunicative; V81998 indicates that the patient is not registered with a GP surgery, and that it is not

applicable, owing to the patient being a recent immigrant (for example); V81997 indicates that a patient is eligible, but not registered with a GP surgery; in addition some records in the register are simply coded null, indicating that a record was not made. Table 8.2 indicates how recording of patient's registered GP surgery varies across years by inpatient and outpatient, there is a rebound in the percentage of admissions which do not have an associated GP surgery marker post 06/07 for both inpatient and outpatients which is interesting, and may reflect different data quality regimes.

<i>Year</i>	03/04	04/05	05/06	06/07	07/08	08/09
Inpatient						
(No. of GP surgeries)	4852	4989	5087	5368	5187	5333
% Admissions with no GP Surgery record	4.41	4.29	3.57	2.99	4.17	3.58
Outpatient						
(No. of GP surgeries)	6602	6803	7104	7236	7308	7433
% Admissions with no GP Surgery record	4.14	4.05	3.48	2.95	3.25	3.36

Table 8.2: Number of unique GP surgeries recorded for London inpatients and outpatients, and percentage of admissions missing GP surgery record, by year.

According to the NHS Quality and Outcomes Framework data for 08/09 there are 1,541 GP surgeries in London. However, this figure is significantly lower than the observed number of GP surgeries that London residents are registered with, evidence perhaps of the lag in the NHS's ability to capture residential mobility in its primary care registration data, or of the transience of some London inhabitants. This is evident in Figure 8.4 which demonstrates the long-tail of GP surgery registrations for London in- and outpatients where a GP surgery is listed.

There is almost no difference between the cumulative percentage distributions of inpatient and outpatient admissions by registered GP surgery. What is interesting, however is that in both cases the first 1500 GP surgeries account for c.97% of all admissions, and the first 1650 c. 99% - these are the London-based GP surgeries, with some edge effects caused by GP surgeries just outside of the London boundary.

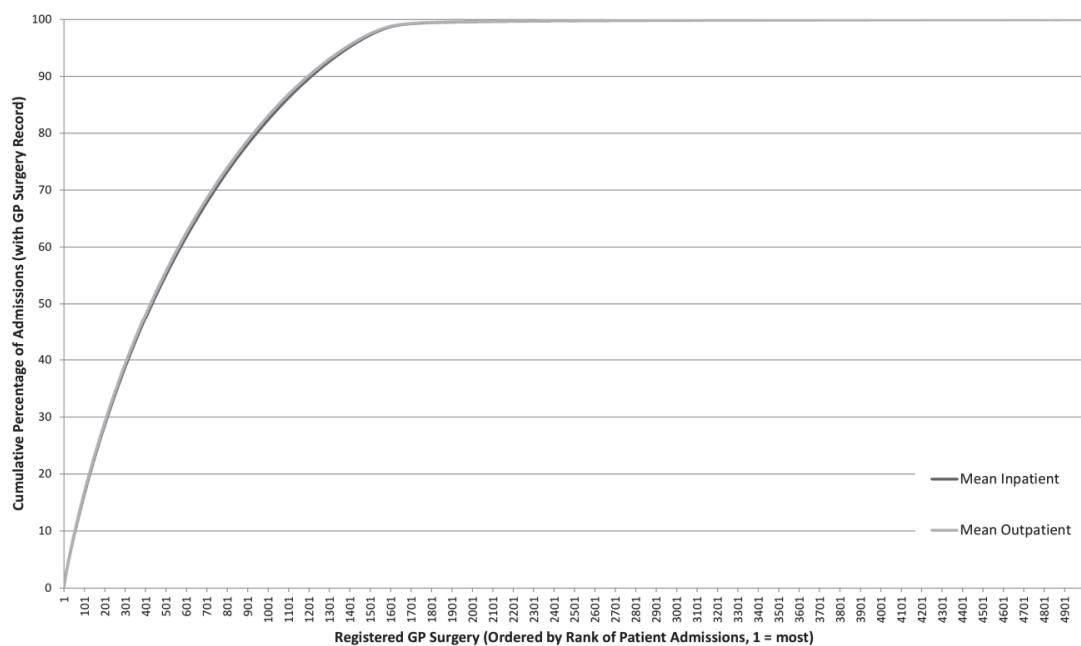


Figure 8.4: Cumulative Percentage Admissions by GP Surgery for Inpatients and Outpatients, mean for all years.

In the next section, the spatial patterning of London inpatient and outpatient data is considered at the LSOA level in order to unpick the aspatial patterning of care presented in this section. This is done both in terms of admission rates by LSOA, and road network distance to provider.

8.4.2 The Spatial Patterning of Hospital Care in London

The NHS, subject to the proposed systemic changes enshrined within the Health and Social Care bill, is placing increasing importance on local context with regard to population health and healthcare. It is the role of GPs to look after the primary care needs of the local communities which they serve, regardless of whether the commissioning is coming from Primary Care Trusts, or the envisioned GP consortia. The government perceives a requirement to cater for individuals in their local communities, whatever and wherever they may be, and yet it also has a requirement to provide an equitable service on a national basis based upon need. The NHS cannot actively privilege certain geographical areas over others, just as it cannot privilege the rights of people based on wealth or ethnicity. It has been noted however, in health (cf. Marmot Review, 2010) and socially (cf. Dorling, 2010b) that particular policies, and patterns of service, can lead to unjust circumstances for different population groups. This is a situation that is often recognised by service users through the

media as a 'postcode lottery', a situation in which people living in one area have privileged access to care that those living elsewhere do not.

In providing health care services there is a principal need, enshrined in the NHS Constitution (DH, 2010a), to provide a local service. Analysing patterns of hospital admissions at a local level of geography - in this case the Lower-Layer Super Output Area (LSOA) - implies that the research is predicated on the idea that there exists a spatial relationship between health inequalities and local areas. Such relationships have been widely evidenced, particularly between the richest and poorest members of society. This in mind, it is not enough to characterise local areas as deviant (somehow) from a national average value for each dimension of health inequality, rather it is desirable to compute a local rate and investigate how such a rate is distributed. This is a metric that allows a local viewpoint (provision of health care is a local service), whilst allowing for wider disparities to become evident (health is a local services that should be equitable at the national scale across all localities). In this section inpatient admissions are focussed on due to the inadequacy of geographical coding for outpatients.

8.4.2.1 Relative Risk

A useful way of interpreting the health status of an area is to examine relative risk. Relative risk is generally approximated by taking the ratio of people that actually experienced an event, such as a hospital admission, by the number of people that might be expected to experience such an event. As such relative risk is calculated as:

$$\text{Relative Risk} = \frac{\text{Observed number of events}}{\text{Expected number of events}} \times 100 \quad (8.1)$$

The expected number of counts is the benchmark expectation of the area, so a value of 100 conforms to expectations, a value below 100 indicates that the area does better than expected, i.e. has a relative risk of an observed event lower than the benchmark, and a value higher than 100 indicates that the area is doing worse than expected.

In order to calculate the expected number of events, the risk ratio of observed events (i.e. at national level) is applied it to the population of the local area. This is a case of finding the ratio of people in an area who experienced an event over the population at risk of the event:

$$\text{Risk} = \frac{\text{Observed number of events}}{\text{Population at risk}} \quad (8.2)$$

Risk is usually expressed as a value per a certain number of people (e.g. 14 per 1000), although it is not an appropriate measure for identifying relative risk for local areas as the demographic composition of areas is variable. Certain sub-groups of the population are more susceptible to particular events than others, and as such an estimate for an area which comprises a large proportion of a susceptible population group should accordingly have a higher expected value in the relative risk calculation.

In order to account for demographic variability in areas, indirect age and sex standardisation is used. This means that a specific risk is created for each age and sex band at the aggregate level, which can then be applied to the specific population to which it is relevant in the local area. An expected value is calculated using indirect standardisation in the following way:

$$\textit{Expected} = \sum \textit{age band \& sex specific risk} \\ \times \textit{age band \& sex specific local population} \quad (8.3)$$

Where the sum indicates the sum of all required age bands and sexes by their local populations.

In this way a relative risk can be created that is relevant to a given risk. In many cases it is risk at a national level which is used to estimate local relative risks, but for a sufficient number of observations, risk ratios computed for different regions could be used, although this would only be applicable spatially if the local areas nested within the regions. There is an argument for using regions, particularly if they have relevance to the properties being measured.

Under the NHS an argument could be made for indirectly standardised relative risks for local areas using risk ratios derived from Primary Care Trust (PCT) or Strategic Health Authority (SHA) areas as they are responsible for commissioning and managing care in these areas.

Inpatient admissions rates are computed for London at LSOA level using expected values derived from London as a whole, for each year. The Office for National Statistics mid-year LSOA population estimates are used as the base for computing risk values, allowing for variation in population from year to year, which could be associated with fluctuations in local admissions, to be taken into account. A visualisation of the results is shown in Figure 8.5, in which the standardised admission rate for each LSOA is classified in terms of its standard deviation from the mean of the data (which due to the indirect standardisation is 100 in each case). The annual data demonstrates a consistent pattern of above- and below-average

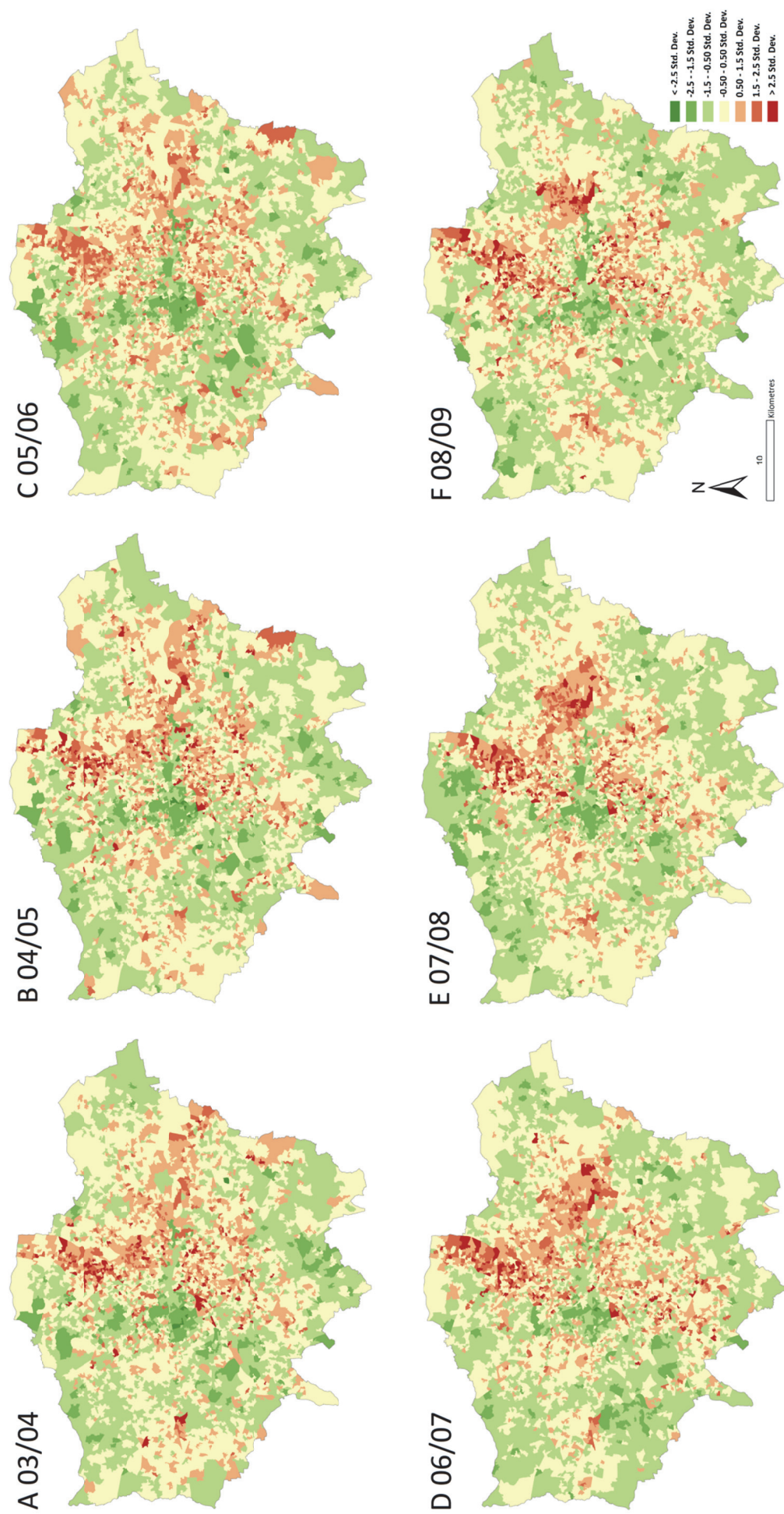


Figure 8.5: Small multiple (A-F) showing indirectly standardised inpatient admissions rates for London, derived from HES data. Indices are relative to the London average.

inpatient admissions rates in particular LSOA compared to the London average.

The relative risk of admission to inpatient care indices visualised in Figure 8.5 are calculated subject to the total admissions by age and sex for London as a whole, this may be useful if we choose to believe, as might be pertinent, that London is distinct from the rest of the country and deserves to be treated independently. However, under such a belief, we may further choose to believe that the structure of healthcare management and commissioning in London has an important role to play; in this case a spatial approach can be used which uses information on admissions in the neighbouring area, rather than the whole of London, to compute relative risks. This is known as spatial smoothing.

8.4.2.2 Spatial Smoothing

Spatial Smoothing allows for a unique region to be defined for each LSOA within which the locally expected admissions can be enumerated. This means that the relative risk computed for each LSOA is not subject to a London average, but to a local average which may be more pertinent. Spatial smoothing can also employ a distance weighting so that LSOAs that are closer to the LSOA for which a relative risk is being calculated receive a higher weighting than those that are further away.

There are two main type of spatial smoothing that can be used in this context: mean and median based methods. The mean method is simplest, calculating the distance weighted average of the specified number of nearest neighbours for each local area. The risk for a single age band and sex can be calculated as:

$$\text{Age \& sex specific risk at } i = \frac{\sum_j w_{ij} \times \text{Age band \& sex specific risk at } j}{\sum_j w_{ij}} \quad (8.4)$$

Where i is the local area in question, j is one of the spatial neighbours to i , and w_{ij} is the distance weights matrix for i with respect to j . Note that the area in question is also included in this evaluation with $w_{ii} = 1$.

The main issue with using mean spatial smoothing for count data, such as observations of a particular disease, is that the mean can often upwardly bias the expected counts of an event. This is because the distribution of counts is likely to have a long tail; a distribution of count data is effectively constrained by 0 observations in the left tail, but is theoretically unlimited in the right tail. Because the median is the middle value it better approximates where most of the data are, and avoids being skewed by the large outliers in the dataset.

Due to the shape of the distributions of admission data, it is preferable to use a median-based spatial smoothing technique instead. This research implements the iterated median smoothing technique. The basic approach is to take the median value of the set of rates for k nearest neighbours, such that:

$$\text{Age \& sex specific risk at } i = \text{median}(\text{Age band \& sex specific risk at } j), \text{ for all } j \quad (8.5)$$

An iterated variation on this can be made where the candidate area is replaced each time with the newly computed median for the area, known as the iteratively resmoothed median. Anselin et al (2006) suggest a median smoother that is also weighted by population, which can be particularly useful for adjusting rates based on divergent population sizes. It is this method that is used here, as it mitigates the effect of different population group sizes when there is a discontinuity between the area in question and a nearest neighbour. This method works by creating a list of the cumulative sum of weights (here population size for an age and sex band) which are ordered based on the rank of the original ordered admissions data for the k nearest neighbours selected. The weighted median is the value that corresponds to the position in the ordered index of original data that fulfils:

$$\min \{ \text{Cumulative weight at index rank } i \geq \frac{\sum \text{All weights}}{2} \} \quad (8.6)$$

The characterisation of spatial relationships is important to any local spatial operation; however there is no universally accepted way of characterising spatial relationships. Different approaches include: taking a theoretical approach to spatial relationships in which a particular model is supposed; taking a geometric approach in which a representation of spatial proximity is privileged in the absence of theory; or a descriptive approach in which the data in question drives the specification of the underlying spatial relationships (Getis, 2008). In this case a geometric approach is utilised, and polygon continuity is used as the preferred representation of spatial proximity, and the first order is applied meaning that any LSOA that shares a border with another LSOA is considered to be its neighbour. Relative risk of inpatient care admission in London is shown in Figure 8.6 using the spatial smoothing approach.

8.4.2.3 Understanding the Relative Risks of Admission to Inpatient Care

It is clear from Figures 8.5 and 8.6 that 2 distinctly different representations of the patterns of admissions have been created. On the one hand, the series of images in Figure 8.5 seems to

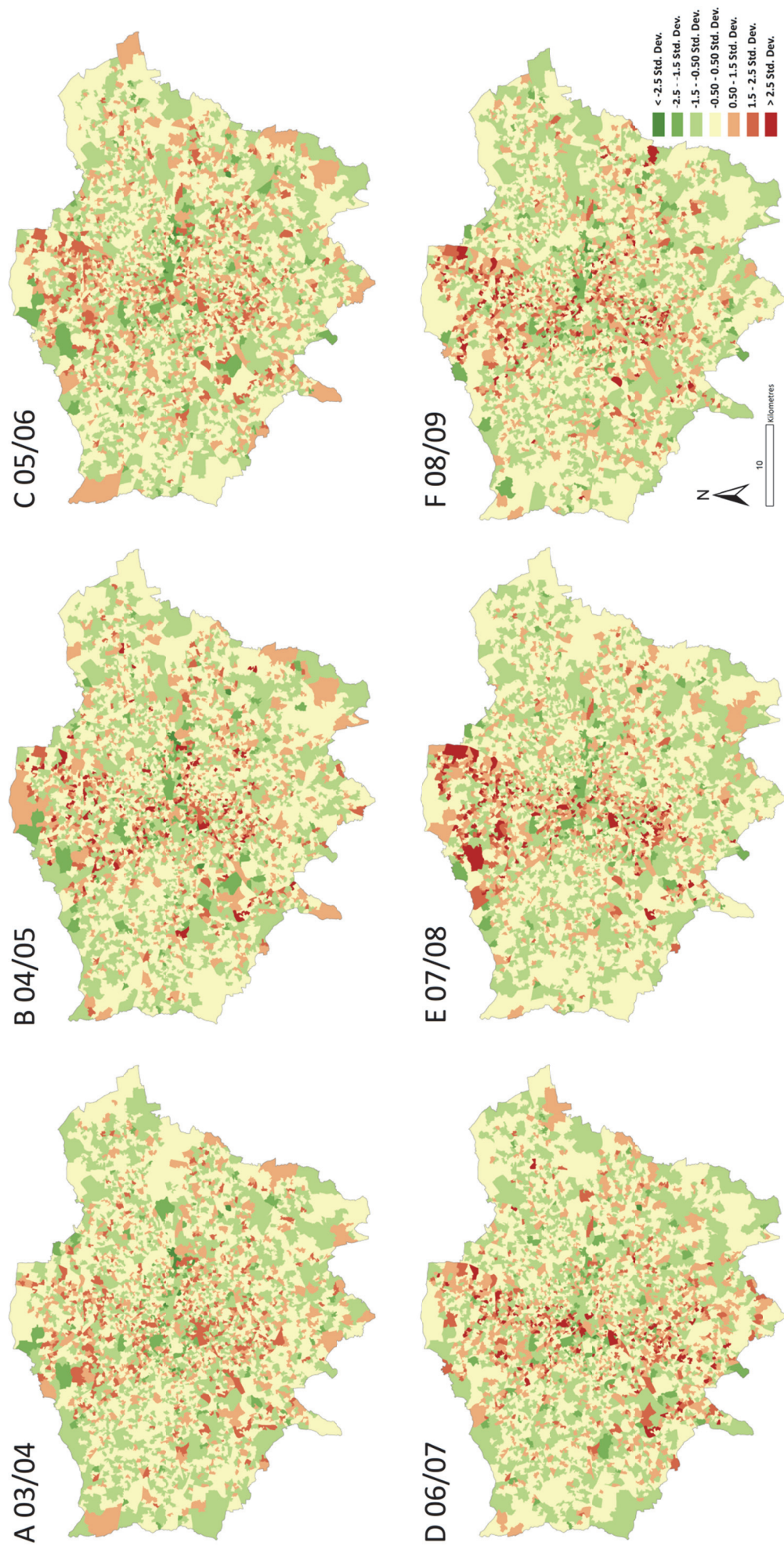


Figure 8.6: Small multiple (A-F) showing indirectly standardised inpatient admissions rates for London, derived from HES data. Indices subject to local averages.

suggest a strong spatio-temporal pattern in the distribution of relative risk of inpatient admission by LSOA compared to London as a whole, with East London and the Lea Valley subject to higher admissions rates than West London. Whereas, on the other hand, Figure 8.6 does not seem to suggest any particularly recognisable, or ordered, patterns of admissions, perhaps with a case for a north-south alignment in some years.

The key difference in the creation of the two visualisations of inpatient relative risks is the spatial context; Figure 8.5 allows for deviations from an expected rate of admissions for all of London, whereas Figure 8.6 allows only for local deviations. This means that areas of consistently high index values, or low index values are suppressed, and areas that are very different from their local contexts are highlighted, in a sense, Figure 8.5 highlights some of the spatial dependency of inpatient admissions, and Figure 8.6 effectively controls for some of that local spatial dependence, foregrounding the areas where relative risk of inpatient admissions is less well explained by local context. These issues are demonstrable by considering the spatial autocorrelation apparent in each spatial distribution of indices using the Moran's I statistic. Moran's I captures the extent to which a spatially distributed phenomenon differs from complete spatial randomness, allowing an assessment as to whether a phenomenon is clustered or dispersed in its distribution of values over space (de Smith et al, 2009). Table 8.3 demonstrates the Moran's I values for the distributions of relative risk in Figures 8.5 and 8.6.

<i>Year</i>	03/04	04/05	05/06	06/07	07/08	08/09
Relative Risk (London)	0.412	0.393	0.417	0.471	0.487	0.451
Relative Risk (Local)	0.058	0.052	0.074	0.095	0.130	0.102

Table 8.3: Moran's I values for relative risk of inpatient admission for London (section 8.4.2.1) and locally (8.4.2.2)

It is important to recognise that in both cases, the Moran's I values in Table 8.3 are evidence of significant spatial clustering at the 1% level. However, it is also clear that the magnitude of this clustering is considerably higher for relative risk in Figure 8.5 than in 8.6. Thus there is evidence for a greater amount of spatial dependence in Figure 8.5. This is apparent if the distribution of relative risks is compared to the distribution of another spatially distributed phenomenon, such as the Index of Multiple Deprivation. Table 8.4 shows the Pearson Correlation Coefficients for each year compared to the Index score for the IMD 2007, which

represents a reasonable near-midpoint estimate of relative deprivation over the period of the hospital admissions data (alternatives would have been IMD for 2000, 2004, or 2010).

<i>Year</i>	03/04	04/05	05/06	06/07	07/08	08/09
Relative Risk (London)	0.644975	0.633544	0.634817	0.649945	0.662698	0.611619
Relative Risk (Local)	0.300473	0.307634	0.303695	0.240003	0.277659	0.298434

Table 8.4: Pearson Product-Moment Correlation Coefficient between Relative Risks and IMD 2007 Score.

Table 8.4 suggests that there is a strong positive relationship between relative risk ratios for London and relative deprivation – essentially as relative deprivation in an area increases, it is likely that the risk of an inpatient admission will also increase. This is a straightforward finding, as it is widely known that deprivation has a significant role to play in people's health outcomes, and this is reflection of that. There is still a positive relationship between relative risk calculated locally and relative deprivation, but it is much weaker, suggesting that when accounting for some of the local spatial dependence in admission relative risks, there are other characteristics that are important to consider beyond relative deprivation. Controlling for, or removing the spatial dependence of phenomena can help reveal important aspects associated with health behaviours that were otherwise hidden by the effect of local spatial autocorrelation: this kind of approach is what has driven the development of Geographically Weighted Regression (Brunsdon et al, 1996), and spatial filtering (Getis and Griffith, 2002).

8.4.2.4 Consolidation

Whilst, an understanding of the demographics and contextual effects that drive patterns of admission to hospital care is useful to healthcare suppliers, it is of perhaps of more importance to an administrative body with a welfare agenda seeking to reduce health inequalities. Instead, a healthcare provider might be more interested in the operational aspects of how people in different areas use healthcare services. At the aggregate patient level, it is useful to extract a spatial impression of multiple usage of hospital services such as is suggested in a global sense for London in Figure 8.2. However, there are no strong spatial patterns to be found in terms of the number of unique suppliers used by patients by LSOA. Of course this is only likely to be the case if accessibility to Hospitals is dramatically skewed with respect to 2 different areas which it is not. Similarly, if we look at the percentage of patients making multiple visits to hospitals who use more than 1 provider, again evidence for spatial pattern is limited, whilst there is some limited evidence to suggest that patients in

Inner London are less likely to use more than 1 provider than patients in Outer London, particularly North-West and the western extremities of Outer London, this is likely explained by demographic differences.

8.4.3 Competition between Hospital Trusts

There are several ways in which the spatial interaction of patient with provider can be visualised and understood. In this section: network distance and LSOA-based percentage usage maps are demonstrated. The focus is placed on hospital providers listed by NHS London as they constitute the vast majority of admissions, thus 20 NHS acute trusts and a further 9 foundation hospital trusts are selected, and the recorded inpatient and outpatient admissions data for each year are extracted and geocoded. In this way much of the variation in local usage of hospital care can be captured.

8.4.3.1 Geocoding NHS Trust Providers

The current London Strategic Health Authority (SHA), responsible for strategic leadership for London NHS services, lists 20 NHS acute trusts, and a further 9 hospital foundation trusts within London, excluding mental health orientated trusts. These are listed in Table 8.5, including inpatient and outpatient admissions for 2008/2009. In each case the main associated hospital(s) are also listed, and the relevant NHS provider code is given as an indicator of the aggregation of services by provider. In some cases multiple hospitals are accounted for by a single provider code, whilst in others multiple provider codes account for multiple hospitals subject to a single trust. In the second case, multiple codes for a single supplier indicates previously independent trusts which have merged since mid-2009. Where the type is prefixed with "special", this is an indication that the trust in question occupies a particular specialist healthcare sector. Within London there are five examples: Great Ormond Street Hospital; Royal National Orthopaedic Hospital; Moorfields Eye Hospital; Royal Brompton Hospital; and Royal Marsden hospital. These special trusts focus on: children; orthopaedics; eyes; heart and lung treatment; and cancer treatment, respectively. As many other London trusts also specialise in particular treatment areas, the five special trusts have not been excluded, however it makes sense to be aware of them as they may have distinctly different admission characteristics to more general medicine focused hospitals.

Each NHS provider code is linked to a particular hospital or group of hospitals, thus each patient admission requires a patient visiting a physical location in order to receive treatment.

NHS Code	Name (- Main Hospitals)	Type	Patient Admissions 08/09	
			Inpatient	Outpatient
RF4	Barking, Havering & Redbridge Hospitals NHS Trust - Queen's Hospital, Romford - King George Hospital	Acute	136,499	711,917
RVL	Barnett & Chase Farm Hospitals NHS Trust - Barnett Hospital - Chase Farm Hospital	Acute	89,789	475,550
RNJ	Barts & the London NHS Trust - St. Bartholomew's Hospital - St. Paul's Hospital - The Royal London Hospital	Acute	85,220	585,523
RJ6	Croydon Health Services NHS Trust - Croydon University Hospital (Formerly Mayday University Hospital)	Acute	72,600	400,741
RC3	Ealing Hospital NHS Trust - Ealing Hospital	Acute	49,447	291,148
RVR	Epsom & St. Helier University Hospitals NHS Trust - Epsom Hospital - St. Helier Hospital	Acute	62,393	409,283
RP4	Great Ormond Street Hospital for Children NHS Trust - Great Ormond Street	Special Acute	13,584	80,978
RYJ	Imperial College Healthcare NHS Trust - Charing Cross Hospital - St. Mary's Hospital	Acute	168,974	923,139
RAX	Kingston Hospital NHS Trust - Kingston Hospital	Acute	59,141	269,559
RJ2	Lewisham Healthcare NHS Trust - University Hospital Lewisham	Acute	56,474	249,717
RNH	Newham University Hospital NHS Trust - Newham University Hospital	Acute	66,116	235,929
RAP	North Middlesex University Hospital NHS Trust - North Middlesex University Hospital	Acute	53,418	292,687
RV8	North West London Hospitals Trust - Northwick Park Hospital - Central Middlesex Hospital	Acute	96,815	381,007
RAL	Royal Free Hampstead NHS Trust - Royal Free Hospital	Acute	156,777	675,249
RAN	Royal National Orthopaedic Hospital NHS Trust - Royal National Orthopaedic	Special Acute	4,965	40,335
RYQ	South London Healthcare NHS Trust	Acute	(160,641)	(834,873)

RG2	- Queen Elizabeth, Woolwich		52,382	255,751
RG3	- Princess Royal University Hospital		70,173	386,814
RGZ	- Queen Mary's, Sidcup		38,086	192,308
RJ7	St. George's Healthcare Trust - St. George's Hospital	Acute	104,981	483,190
RFW	West Middlesex University Hospital NHS Trust - West Middlesex University Hospital	Acute	49,059	307,468
RGC	Whipps Cross University Hospital NHS Trust - Whipps Cross University Hospital	Acute	74,450	296,624
RKE	Whittington Hospital NHS Trust - Whittington Hospital	Acute	53,144	379,657
RQM	Chelsea & Westminster Foundation Hospital NHS Trust - Chelsea & Westminster Hospital	Foundation	67,606	425,719
RJ1	Guy's & St. Thomas NHS Foundation Trust - Guy's Hospital - St. Thomas's Hospital	Foundation	156,816	814,080
RAS	Hillingdon Hospitals NHS Foundation Trust - Hillingdon Hospital - Mount Vernon Hospital	Foundation	53,645	254,085
RQX	Homerton University Hospital NHS Foundation Trust - Homerton Hospital	Foundation	50,004	244,597
RJZ	King's College Hospital NHS Foundation Trust - King's College Hospital	Foundation	107,608	658,188
RP6	Moorfields Eye Hospital NHS Foundation Trust - Moorfields Eye Hospital	Special Foundation	22,515	253,292
RT3	Royal Brompton & Harefield NHS Foundation Trust - Royal Brompton Hospital - Harefield Hospital	Special Foundation	14,010	79,806
RPY	Royal Marsden NHS Foundation Trust - Royal Marsden Hospital	Special Foundation	29,269	137,176
RRV	University College London Hospitals NHS Foundation Trust - UCLH	Foundation	82,058	829,368

Table 8.5: NHS London hospital providers, listing NHS provider code, main trust hospitals and inpatient and outpatient admissions for 2008/2009.

The NHS links each provider code with a physical location, usually associated with the performance of headquarters administrative tasks, however, more often than not the address relates directly to the institution in question. In fact all NHS Trust provider codes for London patients relate to hospitals, however some providers have two or more locations, as is evident in Table 8.5. However, without a more specific indicator of the site at which a patient was treated, the NHS reported provider address is used to geocode the location of providers. The years in question from 2003 to 2009 do show shifting numbers of institutions, however as noted previously these tend to be due to the enumeration of treatment centres not previously recorded.

<i>Year</i>	03/04	04/05	05/06	06/07	07/08	08/09
Inpatient	94.36	94.55	94.90	95.65	96.04	95.94
Outpatient	93.91	93.96	94.28	94.04	94.32	93.26

Table 8.6: Percentage of admissions to NHS London trust care providers that fall within London.

Extending this analysis beyond the years studied here is likely to cause problems as the number of NHS Trusts merging begins to become an issue, and will continue looking further forward as Trusts are required to submit to Foundation Trust status. Table 8.6 demonstrates the percentages of admissions using the NHS London trust providers in each year. It is evident that to a large extent London is a closed-system in terms of admissions to either inpatient or outpatient care.

8.4.3.2 Network Distance to NHS Trust Providers

An insight into how far patients travel in in order to receive care allows for a spatial characterisation of the choices that patients are making with regard to hospital care. Using the provider locations listed in Table 8.5, an attempt to characterise the distance travelled per admission for each LSOA was sought. In order to do this, the network distance between the population-weighted LSOA centroid for each LSOA and the location of each NHS trust provider code, geocoded by their postcode, was calculated. The Ordnance Survey Meridian 2 road network was used for computing the shortest path distance. Figure 8.7 shows the relationship between inpatient admissions and distance from NHS providers for London.

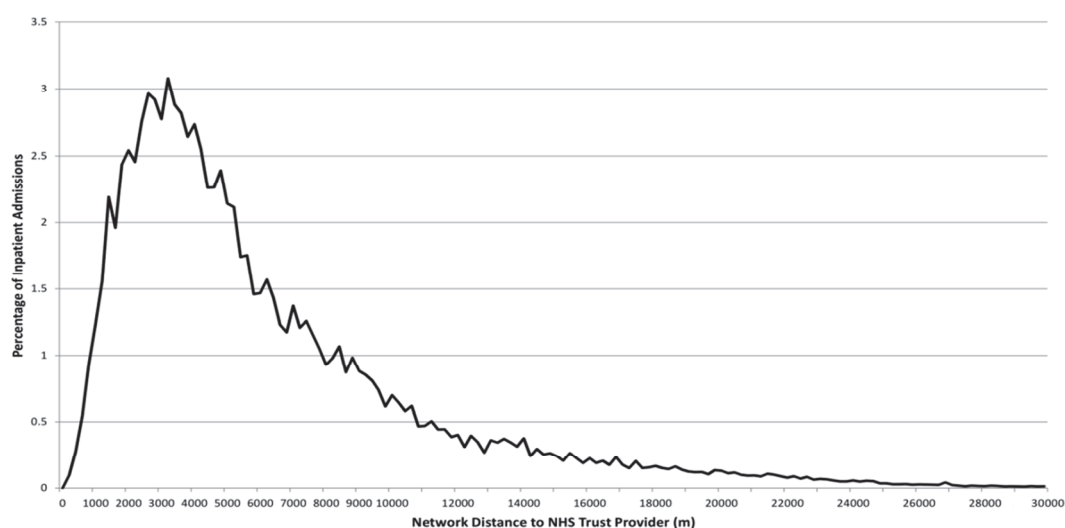


Figure 8.7: Distance decay curve for percentage frequency of inpatient admissions to the NHS London hospital trust providers by network distance, averaged for all years 2003/04 to 2008/09.

As with GP surgery registrations in Southwark, the shape of the distance decay curve for admissions to hospital care is roughly log-normal. It demonstrates a modal distance of around 3,600 metres, and is characteristically long-tailed by virtue of a minority of hospital admissions for which patients have to travel a considerable distance to attend. Further, the average distance travelled for an admission was calculated for each LSOA for inpatients for each year, subject to the particular set of providers available. Figure 8.8 visualises the results for inpatients by distance quintiles with the appropriate NHS Trust provider locations overlaid for each year. The pattern of distance travelled to admission for inpatients demonstrates a spatial variation in admissions that is consistent with local usage of hospital services. Further, there is a distinct Inner London bias in terms of shortest path distance; this reflects the density of service provision extant in London.

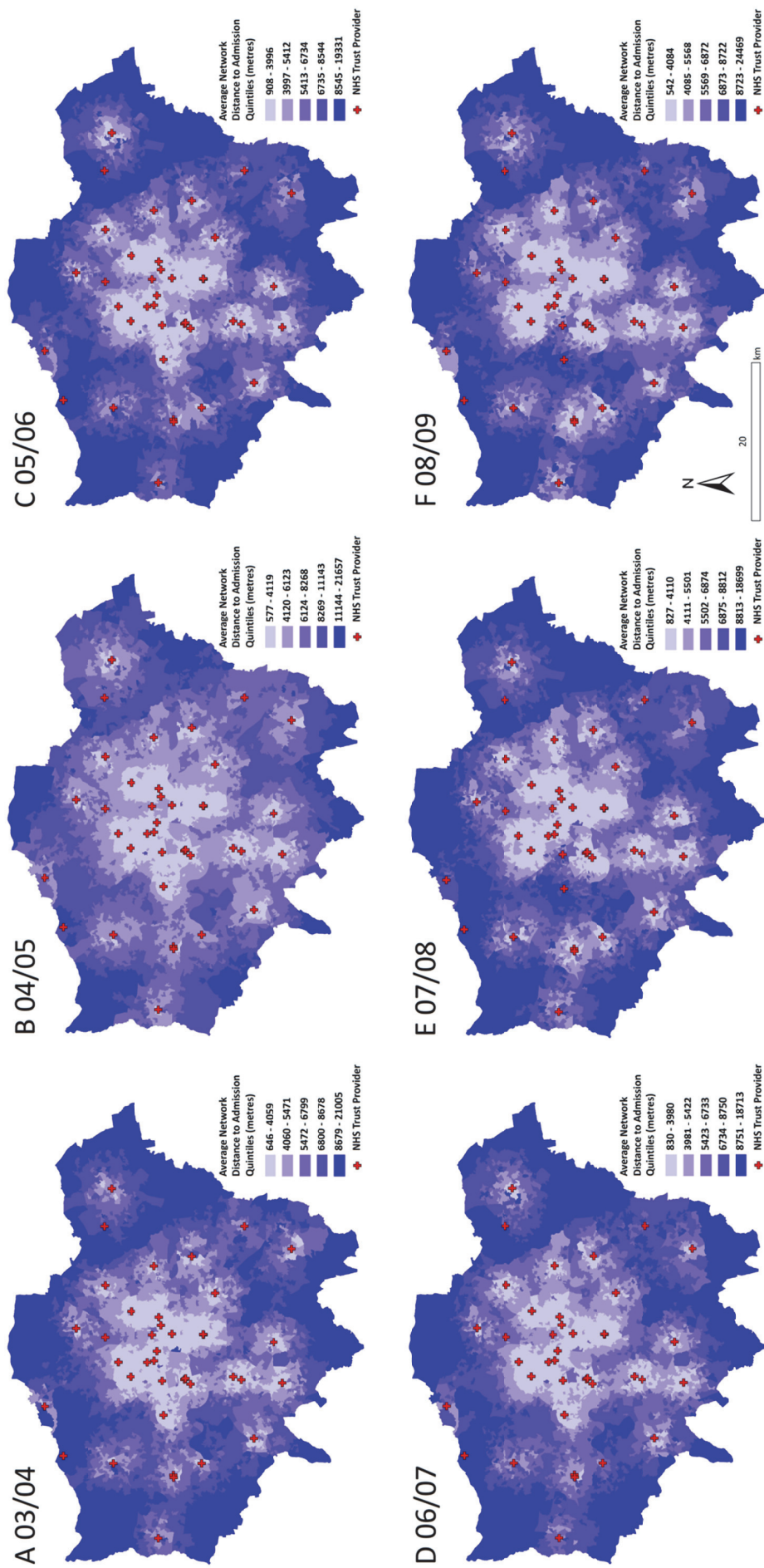


Figure 8.8: Spatial variation in distance to provider aggregated by inpatient admissions by LSOA

8.4.3.3 Percentage Usage Maps

Aggregate patterns of usage, or distance travelled to attend an admission, do not reveal particularly strong insights into presence or absence of competition between providers, and tell individual providers comparatively little about their position in the market. Further, the information in this section may well be biased by the supposition that the provider location given by the NHS is an accurate representation of the location of the provider given the possibility of: multiple hospitals; community-based care; and specialist treatment centres based in regional locations as satellites of a main hospital.

Instead, it might be more pertinent to map the distribution of percentage admissions to a particular NHS Trust Supplier by LSOA, which removes the potentially faulty focus on distance. Because the data can be disaggregated for London down to the LSOA level, which is a small areal level of spatial location, patterns implicit in the distribution of admissions can be detected. Figure 8.9 shows the distribution of outpatient admissions percentages for two proximal NHS Trusts in North London – Figure 8.9A is the Royal Free Hampstead Hospital, and Figure 8.9B is the Whittington Hospital in Archway. We might expect that two nearby NHS Trusts might consider themselves as being in competition with one another for patients, and mapping their patient distributions by LSOA may give a greater insight into whether this is the case. According to Figure 8.9, there seems to be a basis for supposing competition between these two providers, certainly neither hospital is at the median centre of its distribution of outpatient admissions, and the patterning of admission seems to dovetail together.

The overriding positive of the approach is its simplicity. It is difficult to make an assessment of extent or significance of competition between providers based upon individual choropleth mappings. Further, considering the density of service in London many individual maps would be required in order to gain even a partial view of the pattern of admissions for a single year of data. It is likely that the complexity of admissions to inpatient, or outpatient care will likely be challenging to unpick using a method such as this.

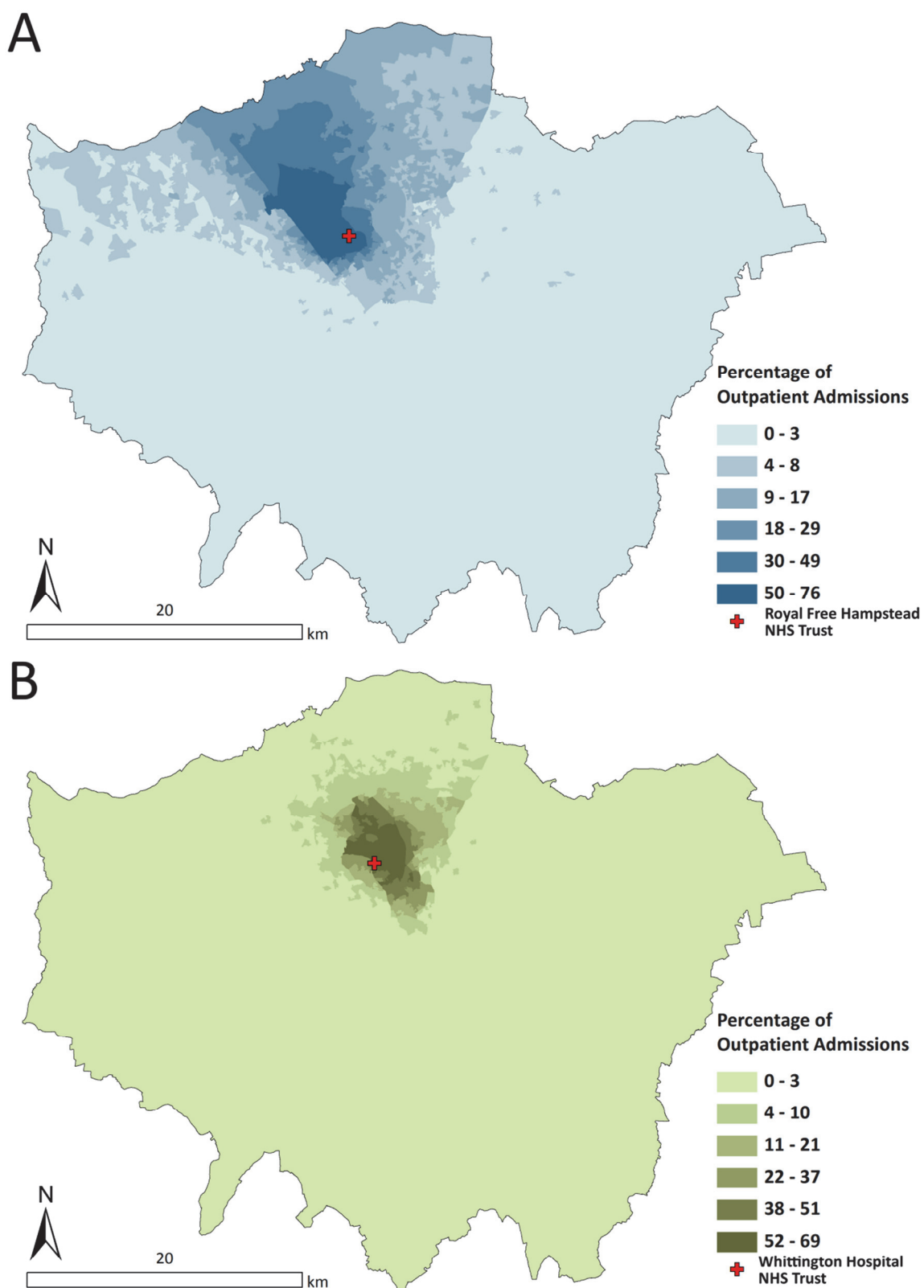


Figure 8.9: Percentage of outpatient admissions by LSOA for 08/09, for Royal Free Hampstead (A) and Whittington Hospital (B) NHS Trusts.

8.4.3.4 Consolidation

Network distance approaches, and percentage usage views of NHS Trust provider admissions allows a simplified view of the geography of inpatient and outpatient care. There are undoubtedly situations in which such approaches are valuable, and they offer some scope for comparative analysis. However, it is felt that in a climate of competition, a more pluralistic approach is more suitable to representing and unpicking interactions between providers. Therefore, the next section focuses on determining service areas for NHS trusts, and examines aspects such as their congruence in order to gain a better insight in to the complex and competitive system of hospital care in London under the NHS.

8.4.4 Hospital Trust Service Areas

This section demonstrates that the service area delineation technique outlined in Chapter 6, and utilised on individual-level primary care data, spatially referenced at the building level, to derive GP surgery service areas in Southwark, is also applicable for use in the context of hospital care across London. This provides a novel and intuitive spatial representation of NHS Trust influence and congruence.

8.4.4.1 Deriving NHS Trust Service Areas

As has been previously described in Chapter 6 (6.3.2) in the context of primary care, the process of service area delineation employed first derives a surface from the spatial patterning of patient admissions for a given NHS provider using kernel density estimation. Subsequently, this density surface is contoured so that the smallest area which represents a given percentage of the density of admissions for that provider is delineated. As in Chapter 6, the bandwidth was given due consideration as its correct specification is the most important aspect of using the KDE technique, out of the options available (see Chapter 6: 6.3.2.2) the normal optimal smoothing equation was used, with a specification of spread subject to the average absolute deviation (AAD) rather than the standard deviation. An Epanechnikov kernel was used due to its availability within ArcGIS 10. The service areas were derived using a consistent 100m cell size, in order to capture the local scale of the LSOA level data from which the service areas were being estimated. However, unlike Southwark GP surgeries which only drew patients from as far away its immediately neighbouring boroughs; larger, particularly nationally focussed hospital trusts drew patients not just from London but from its surrounding area, and at times England as a whole. This meant that density surfaces were frequently calculated for much of the South-East of England, or larger,

meaning that the number of cells in the resultant raster was larger than could be accommodated using a 32-bit computer architecture, thus processing was conducted in 64-bit python. The large file sizes meant that it could take up to a week to calculate the set of 50% and 80% service areas for all London SHA NHS trusts listed in Table 8.5 for all years for outpatients, and several days for the inpatient data which has fewer recorded admissions.

8.4.4.2 Analysing NHS Trust Service Areas

Service areas were created to capture 50% and 80% and the density distribution of admissions to each NHS Trust provider. The 50% interval, it was felt provided an insight into where the core local admissions came from, whereas the 80% interval represented the largest the service area could grow whilst still delineating a consistent area from year to year. In terms of mapping and analysing the service areas of NHS trust providers, it is important to consider the area within which a consistent majority of patients are drawn. Figure 8.10 shows the overlaps created for the 50% and 80% service areas for London outpatients; the hospitals marked as “special” in Table 8.5 are omitted from this map as their specialised foci mean that they tend to have very large service areas, and do not provide general out- or in-patient procedures. Figure 8.10 reinforces the observation that London is relatively self-contained when it comes to hospital care, Figure 8.10B representing the 80% service areas effectively delineates the built up area of London, only extending beyond the Greater London Area boundary for a few nearby towns, particularly to the north of London. What is also clear is that service area overlaps are highest in number in Inner London. Given that the service areas are derived from the spatial patterning of admissions, this suggests that these areas are better placed to choose between several local hospital services.

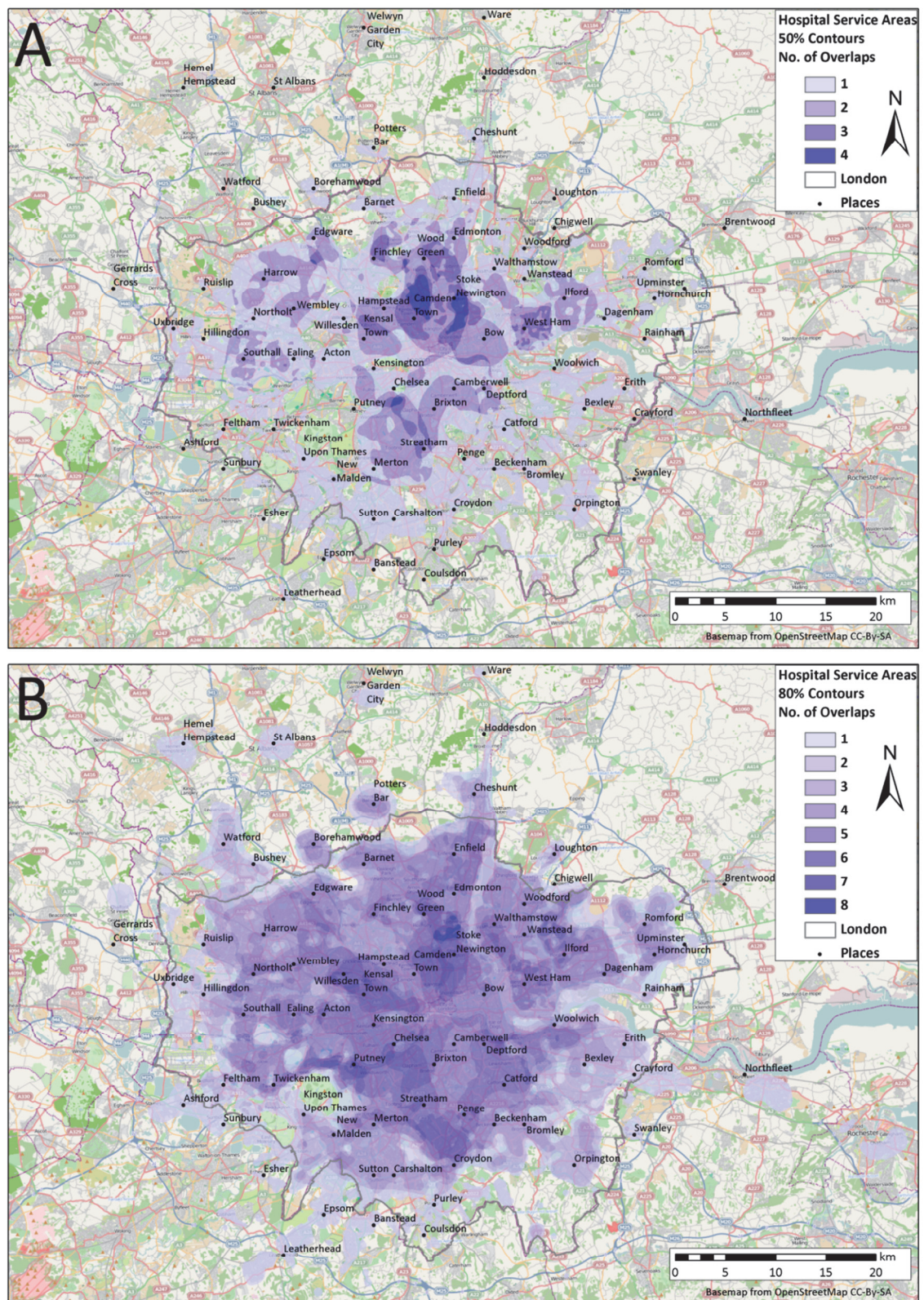


Figure 8.10: Overlapping NHS Trust service areas for 25 NHS London trusts (excluding “special” trusts), for outpatient in 08/09.

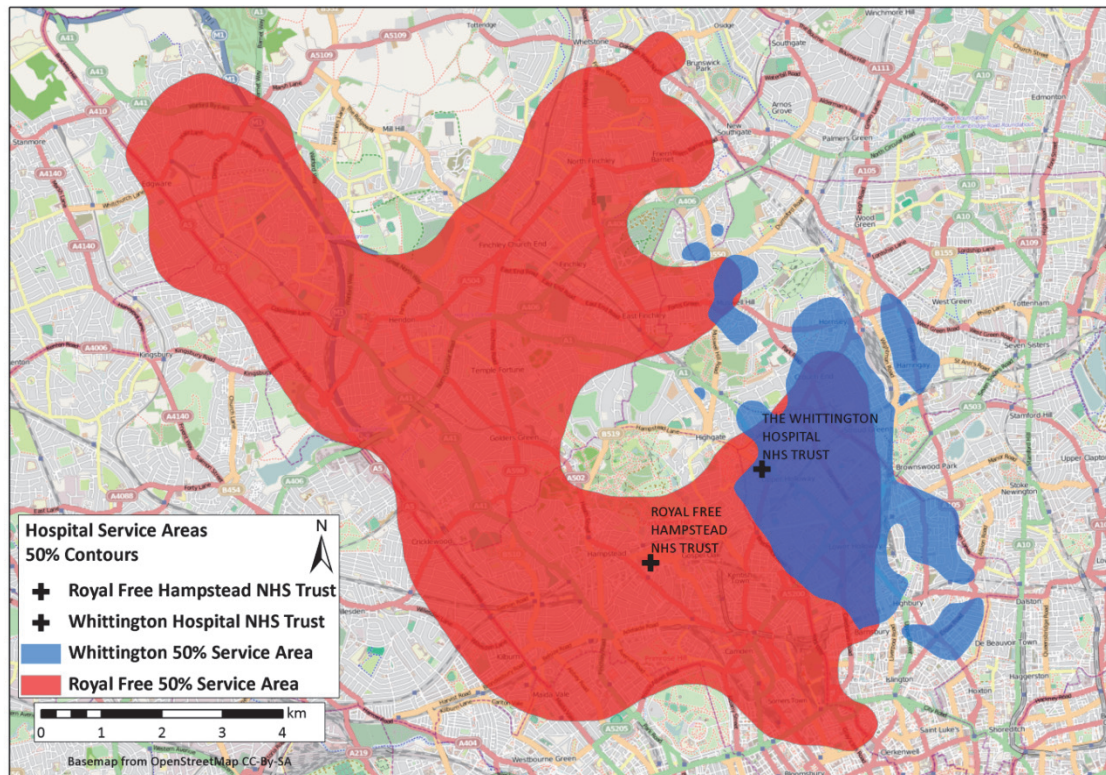


Figure 8.11: 50% outpatient service areas for two North London Hospitals.

It is also useful to visualise individual service areas, in Figure 8.11 the hospital trusts previously described in Figure 8.9 are shown as having overlapping outpatient 50% service areas for 08/09. The differential in size of the service areas reflects the differing numbers of admissions in each hospital – with the Royal Free subject to roughly twice as many in 08/09 as the Whittington, as per Table 8.5. The size of the area bounded by each NHS Trust provider’s service area can give us an idea of the variation across London in the spatial extent of service provision. Figure 8.12 shows the histogram of service areas by their area for inpatients and outpatients the 50% and 80% contours, it demonstrates that the majority of NHS trusts tend to be small, providing local care to distinct areas, whilst a minority of trusts have a greater spatial extent of provision that extends across the London region. The two NHS Trusts that exhibit the largest service areas are University College London Hospitals NHS Foundation Trust (UCLH) and Guy’s and St. Thomas’ NHS Foundation Trust, both of which offer extensive specialised services as world leading teaching hospitals, section 8.4.4.4 demonstrates how specialisms can be treated individually to derive disaggregate service areas. There is a strong positive correlation between inpatient and outpatient service area size ($r = 0.993$ for the 50% contours and $r = 0.974$ for the 80% contours). The correlation between the 50% and 80% contours for each provider is positive and similarly strong ($r = 0.809$ for inpatients, and $r = 0.789$ for outpatients). The area of service areas is also positively

correlated with number of admissions for outpatients ($r = 0.783$ for the 50% contours, and $r = 0.644$ for the 80% contours), but less so for inpatients ($r = 0.613$ for the 50% contours, and $r = 0.240$ for the 80% contours) for 08/09. This may suggest that local admission for outpatients, who may be attending hospital for single day elective surgeries, is much more valuable than for inpatients, who will likely be spending more than 1 day in hospital.

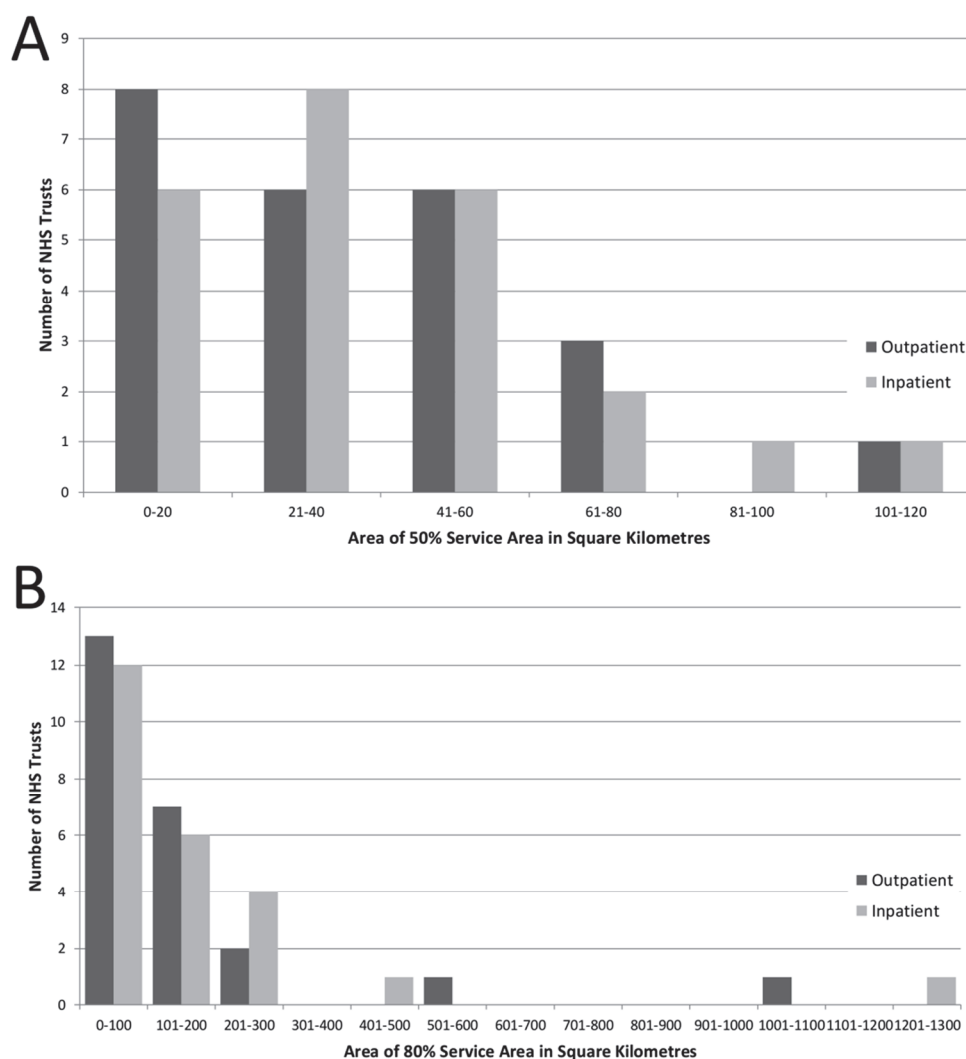


Figure 8.12: Area of London NHS Trust service areas for 50% contours (A) and 80% contours (B) for 0809.

Figure 8.11 also suggests that the Whittington is subject to spatial competition for patients, as the area of overlap reflects the location of patients who have the opportunity to use either hospital. The extent to which different NHS Trusts are likely to experience competition for patients from other Trusts can be gauged by the extent to which their service areas overlap. This can be formally examined by testing for spatial overlay between a service area and all others in a set. Within ArcGIS 10 it is achieved by creating a merged dataset of all service areas for a given percentage contour, and using spatial queries to test for

intersection, the intersect tool can then be used to define the actual size of the congruent area for service area overlaps.

Figure 8.13 shows the histogram of the number of overlaps that each provider experiences with other providers for their 50% and 80% contour service areas. The modal value for providers with overlapping service areas at the 50% level is 0 –no overlaps, however the average number of overlaps is 2.5 (median = 2) suggesting that service over a local area is relatively exclusive at this level, ULCH is again notably different with 9 overlaps. However, at the 80% service area contour level, the average number of overlaps for a provider is 8.25 (median = 7) suggesting that any given provider is likely to have a service area that intersects a number of other providers service areas. UCLH intersects with 23, whilst Guy's and St. Thomas intersects with 20 reflecting their centrality to the system of care in London.

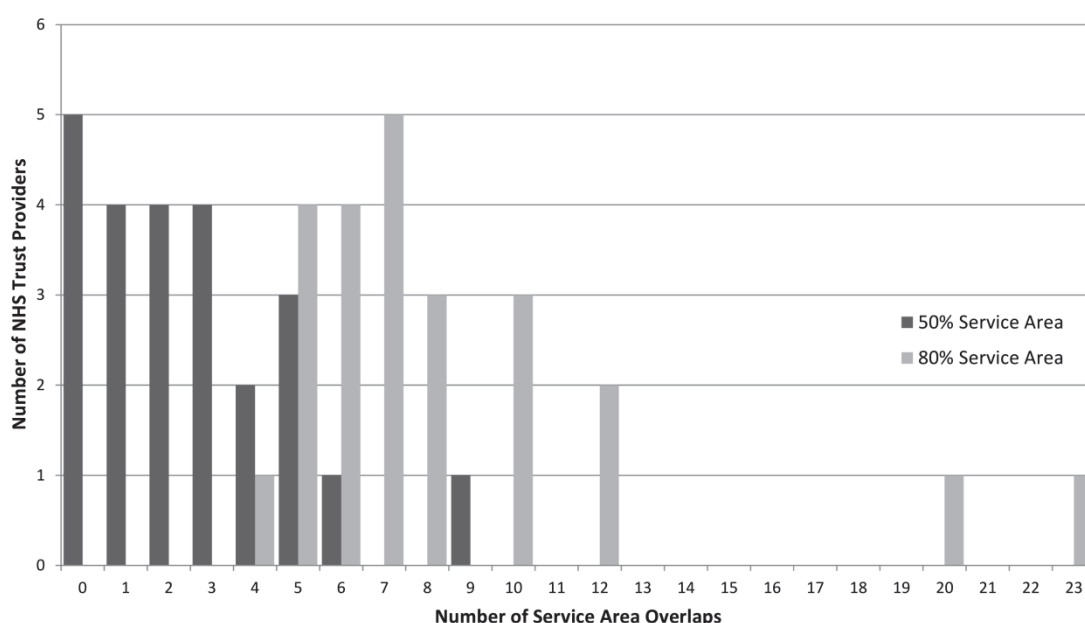


Figure 8.13: Histogram of service area overlaps for NHS London Trust Providers, Outpatients 08/09.

However, simple intersection of service areas are not necessarily that informative – particularly if the amount of overlap that two service areas have is actually very small. Therefore, a clearer insight into the relevance of the service area congruence is gained by looking at the area of the overlap between two provider service areas in terms of the percentage of the total area of the candidate provider that overlaps the other provider. In terms of Figure 8.11, it is clear that to the Royal Free Hospital the overlap represents a relatively small proportion of their service area as a whole, meanwhile for the Whittington

Hospital the overlap is sizable comparative to their total service area. Table 8.7 demonstrates both the number, and magnitude of overlapping service areas for London NHS Hospital Trusts, classifying for each provider the size of the overlap with another provider in terms of the percentage of the first providers total service area that is overlapped. At the 50% level, very few providers are subject to overlaps that amount for more than 20% of their service area size, however, at the 80% level it is clear that most providers overlap with at least one other provider to a majority degree, sharing more than half of their service area with another provider. Thus whilst overlaps are numerous at the 80% service area level, the real competition for patients at one NHS Trust provider is likely to come from relatively few local providers.

Trust	No. of Overlaps 50%	% Congruence					No. Overlaps 80%	% Congruence				
		0 - 20	21 -40	41 -60	61 -80	81 - 100		0 - 20	21 - 40	41 - 60	61 - 80	81 - 100
RJ7	3	3	0	0	0	0	8	3	3	2	0	0
RF4	0	0	0	0	0	0	5	3	0	0	2	0
RJ1	6	5	1	0	0	0	20	17	2	0	1	0
RAL	5	4	0	1	0	0	10	7	2	0	0	1
RNJ	5	5	0	0	0	0	12	7	4	0	0	1
RV8	3	3	0	0	0	0	8	5	0	2	0	1
RJZ	2	1	0	0	1	0	10	5	3	0	1	1
RVL	4	3	1	0	0	0	7	4	1	0	0	2
RGC	1	1	0	0	0	0	6	4	0	0	0	2
RRV	9	8	1	0	0	0	23	20	3	0	0	0
RAX	0	0	0	0	0	0	7	5	2	0	0	0
RJ6	0	0	0	0	0	0	6	2	3	1	0	0
RAP	3	2	0	1	0	0	7	2	2	1	0	2
RJ2	2	1	1	0	0	0	5	2	0	0	1	2
RVR	1	1	0	0	0	0	6	5	0	1	0	0
RQM	4	3	1	0	0	0	10	6	1	0	2	1
RQX	2	0	0	2	0	0	8	3	1	1	1	2
RNH	1	0	0	0	0	1	5	2	0	0	1	2
RAS	1	1	0	0	0	0	4	3	1	0	0	0
RKE	3	1	0	1	0	1	7	2	1	1	1	2
RC3	2	2	0	0	0	0	7	4	1	0	0	2
RFW	0	0	0	0	0	0	5	3	0	1	1	0
RYJ	5	4	1	0	0	0	12	7	3	1	0	1
RYQ	0	0	0	0	0	0	6	4	1	0	0	1

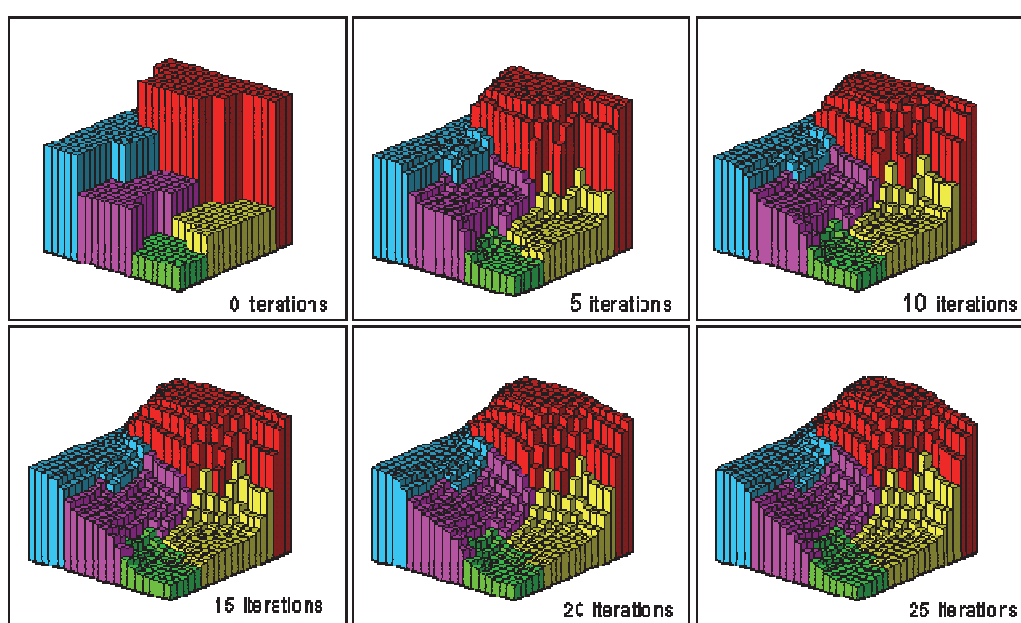
Table 8.7: Spatial congruence of 50% and 80% service areas for London NHS trust outpatients 08/09.

Whilst, it can be enlightening to consider service area overlaps in terms of shared area, particularly as the service areas themselves are derived from the surface estimating the

location of actual admissions, it is actually a lot more pertinent to think in terms of people, rather than geometry; it is after all people that are being provided care.

8.4.4.3 Delineating populations with NHS Trust Service Areas

In order to consider the population bounded by any given NHS Trust service area, the distribution of population underlying that service area is required. In theory the population within the service area can simply be enumerated in order to obtain the service area population. However, service areas are created based on an underlying admissions surface, whereas the population data that is available is zonal, based on LSOAs. Whilst a simple spatial operation could be undertaken to intersect the LSOAs with the service areas the varying extent to which an LSOA could be fully or partially intersected will introduce uncertainty into the enumeration of service area populations. Therefore a surface representation of population is desirable. However, in creating a population surface it is imperative that the actual number of people that the surface represents remains the same, which is not a condition of some surface estimation techniques. Tobler (1979) introduced "smooth pycnophylactic interpolation" (in which pycnophylactic comes from the Greek meaning "volume preserving") as a method capable of creating a smooth population representation based upon zonal data, and it is this method that is employed here.



Pycnophylactic Interpolation

Figure 8.14: Pycnophylactic Interpolation subject to increasing iteration (Source: NCGIA, Date Unknown)

Similar to KDE, pycnophylactic interpolation is a smoothing operation, however, unlike KDE the procedure works by iteratively resmoothing a surface until such a point as the original hard discontinuities between zonal boundaries due to polygon edges are transformed into continuous transitions between zones. This is achieved using a local kernel which averages the local neighbours for each cell, progressively redistributing the cell values. Figure 8.14 shows a practical demonstration of the pycnophylactic interpolation procedure as increasing iterations of smoothing are made.

Figure 8.15 demonstrates the pycnophylactic surface for London generated from LSOA midyear population estimates for 2008. It is created at a 100m raster cell resolution, which mirrors the surfaces underlying the NHS Trust service areas. In order to analyse the set of 50% and 80% service areas derived for London NHS Trusts, a surface of larger extent is created in order to account for the spatial extent of NHS Trust service areas. Using the pycnophylactic surface an estimate of the number of people within each service area can be computed using ArcGIS 10's zonal statistics functions, and subsequently the number of people included in service area overlaps can also be computed.

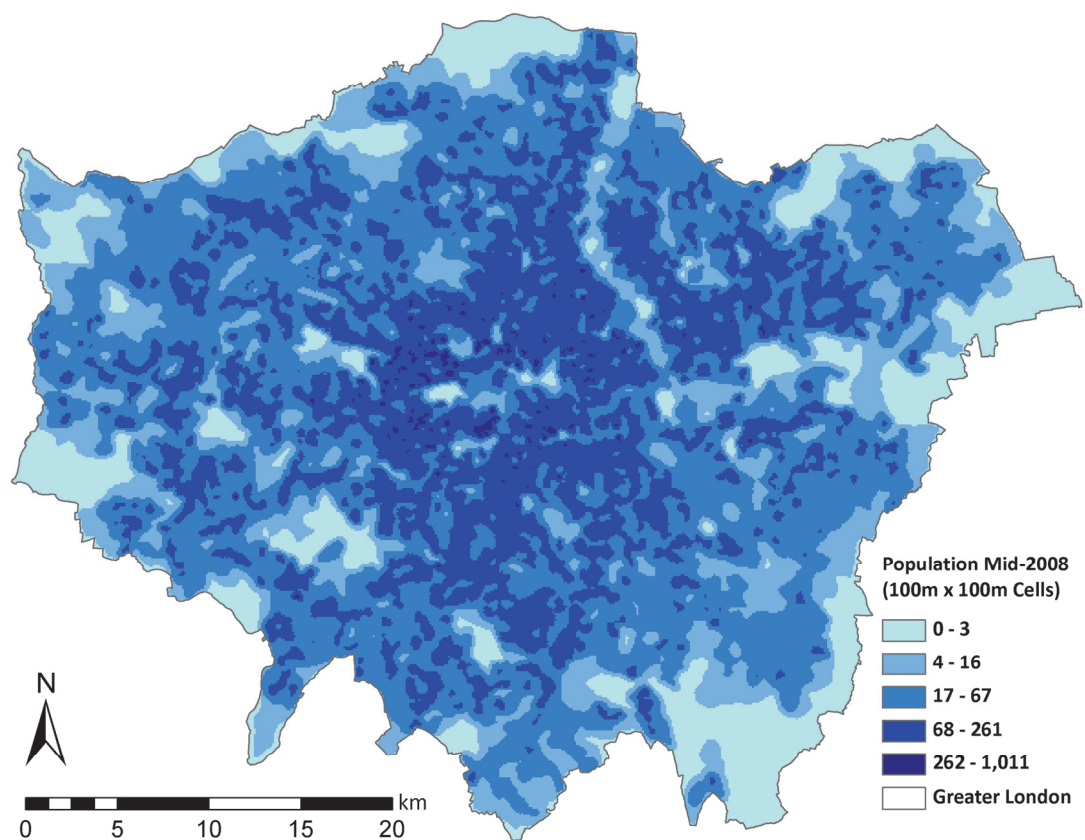


Figure 8.15: Pycnophylactic population surface (100m x 100m cells) for London using ONS mid-2008 estimates

Table 8.8 gives the number of people within each NHS Trust's service area for inpatients and outpatients in 08/09. The average population within the 50%, and 80%, service area contours is around 1/3 of a million, and 1 million people respectively.

Trust	Outpatient		Inpatient	
	No. People 50%	No. People 80%	No. People 50%	No. People 80%
RJ7	306,910	1,011,640	328,781	1,109,480
RF4	338,178	534,977	348,250	544,184
RJ1	635,437	4,341,500	664,342	2,913,650
RAL	592,467	1,928,240	754,534	1,602,380
RNJ	520,097	1,660,860	421,598	1,725,530
RV8	290,768	545,376	311,707	573,108
RJZ	350,450	1,387,590	364,156	1,707,520
RVL	331,474	591,385	335,932	592,836
RGC	199,626	400,285	190,609	328,014
RRV	1,067,940	6,393,270	1,138,220	7,094,980
RAX	186,159	408,779	238,176	438,656
RJ6	189,584	304,589	190,451	324,255
RAP	166,095	354,089	155,011	307,488
RJ2	162,184	307,210	164,797	294,846
RVR	237,045	484,451	252,333	521,131
RQM	272,358	1,354,120	310,868	1,258,040
RQX	148,153	481,037	129,532	249,816
RNH	113,474	194,016	132,595	212,557
RAS	134,127	233,248	152,113	260,134
RKE	166,335	378,514	176,174	402,812
RC3	113,432	226,528	113,986	215,045
RFW	115,129	222,913	140,612	246,740
RYJ	505,128	1,539,620	545,919	1,657,700
RYQ	402,205	660,180	427,587	679,293

Table 8.8: Population totals for NHS Trust service areas at 50% and 80% contour levels for inpatient and outpatients 08/09.

As with the overlapping area in Table 8.7, the population of overlapping areas can also be calculated, in the case of Figure 8.11, for instance the number of people within the overlapping portion of the two service areas is 97,354, equating to 16.4% of the Royal Free Hospital's 50% service area population, but a much larger 58.5% of the Whittington Hospital's 50% service area. These are large populations, signifying potential service recipients; effective NHS Trust oversight will require such knowledge. Particularly in terms of "where?", and "how many?" people are also within the effective service areas of other nearby NHS Trusts. Indeed, it would be relatively straightforward to disaggregate these population totals by population age and sex, even to the extent of generating risk ratios from HES diagnosis records in order to derive a better understanding of local disease burden for

particular conditions or operations. In this vein, the final section broaches the creation of disaggregated service areas by different diagnosis codes.

8.4.4.4 Service Area Delineations by Disease Grouping

It is highly likely that some NHS Trusts will provide specialist services that support national or regional centres of expertise. This has already been alluded to, both in the exclusion from consideration previously of “special” NHS Trusts as recorded in Table 8.6, and in the recognition that UCLH, for example, provides general medical services, as well as having a hospital under its remit that deals specifically with heart conditions. If healthcare planners wish to consider individual service areas separately, because they anticipate different service area sizes for general versus specialist treatments, then this can be achieved by disaggregating the admissions data, and computing service areas subject to the specific density distributions of pre-specified disease groups. In order to test this, the highly disaggregate ICD-10 (International Classification of Diseases, 10th revision: World Health Organisation, 2010) diagnosis codes are generalised using the Clinical Classifications Software for ICD-10 Data (CCS, 2003) allowing for different disease areas to be selected. Unfortunately, the record of primary diagnosis in HES outpatient data is not collected to a sufficient quality to allow for the creation of service areas for outpatients, however, the inpatient record is of higher quality and allows for service area delineation.

Figure 8.16 demonstrates the differing 80% inpatient service areas that are derived for University College London Hospitals Trust when heart-related and non-heart-related primary diagnoses are considered. The heart conditions included, and derived using CCS are: pulmonary heart disease, cardiac dysrhythmias; coronary atherosclerosis; congestive heart failure and myocarditis. There are clearly different spatial foci when it comes to the provision of care to patients dependent upon the conditions being treated; Reading (to the west of London) and Redhill and Crawley (to the south of London) represent important markets for care of heart patients that are not as important in the case of other admissions, and are not present in the creation of a general service area representing admissions for all conditions.

Naturally, it will be the domain of NHS Trust researchers to specify the exact diagnoses of interest to individual Trusts, and it will most likely centre around the particular specialisms that those Trusts offer. Equally, the possibility of miscoding of primary diagnoses, and the

presence of comorbidity through multiple diagnoses, adds to the potential complexity involved in creating these disaggregate service areas. Nonetheless, when used appropriately they may add an additional dimension to the analyses already discussed.

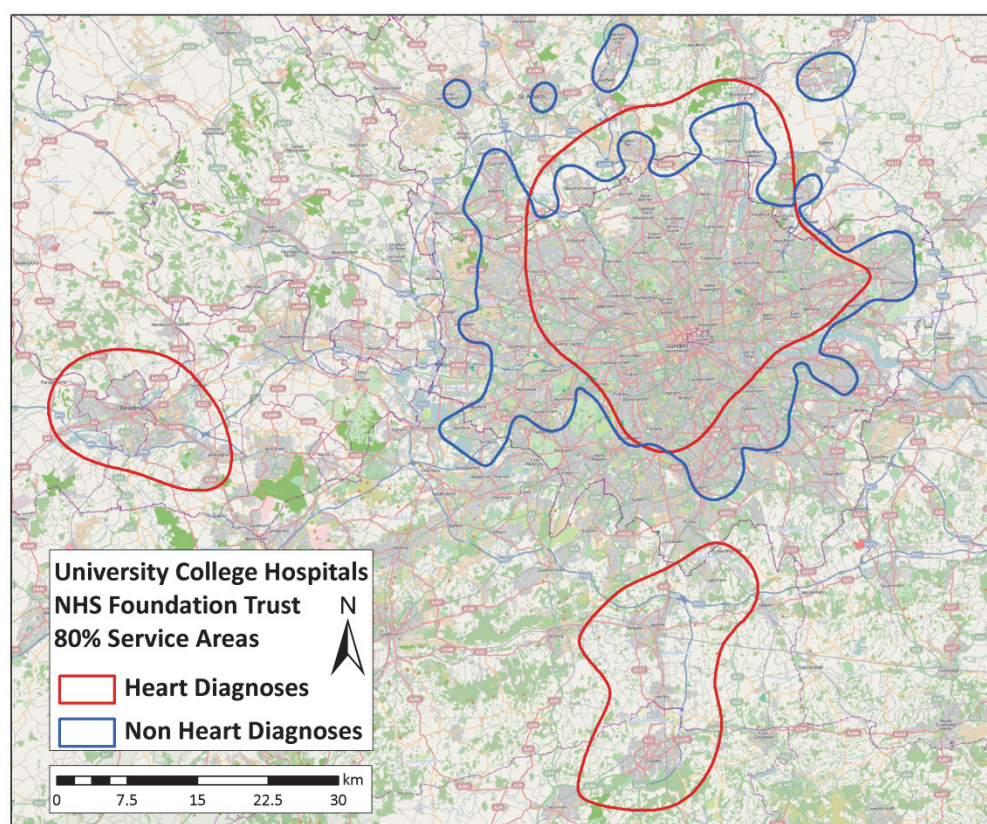


Figure 8.16: 80% service areas for UCLH NHS Foundation Trust for 08/09 for heart-related and non-heart related primary diagnoses.

8.5 Consolidation

This, primarily exploratory, chapter has introduced a broad overview of contemporary and emergent policy as it pertains to the operation of healthcare services, with particular reference to the role and operation of the providers of healthcare, in the NHS purchaser-provider framework. The proposed shift away from the New Labour instituted “cooperation” philosophy in NHS Trust provider relationships, in favour of a probable return to a more overtly competitive system, coupled with the imposed transition of all current NHS Acute Trusts into NHS Foundation Trusts, puts pressure on existing Acute Trusts to manage existing demand for care so as to be eligible for Foundation status, and maintain a cost effective and efficient service. This in mind, the chapter has sought to explore the relevance that spatial analyses have to understanding the patterns of utilisation of hospital inpatient and outpatient care.

Several approaches to characterising patterns of care have been considered, ranging from straightforward areal percentages of admissions, to shortest-path travel distances, and culminating in a discussion of the delineation of NHS Trust service areas. Recent reportage (Ramesh, 2011) surrounding the government's decision to allow a private company, Circle Healthcare, to run Hinchingsbrooke Health Care NHS Trust, responsible for Hinchingsbrooke Hospital, revealed the spatial motives of the founder of Circle Healthcare:

"He pointed out that there were 5,000 patients living within a 'few miles of the hospital that do not use us. That's £5m in lost patient income every year.'" (Ramesh, 2011: No Page Number)

Regardless of the political circumstances that surround the full or partial privatisation of healthcare services, it is clear that such companies value an understanding of local context in delivering an efficient health service. Indeed, much of what has been shown in this chapter corroborates what was stated from the literature in the chapter's introduction – most healthcare providers in London are locally focussed, often providing care to a local area which can be distinctly defined from patterns of patient admission, and which actually have relatively few local competitors. Indeed, London ought to be a context that enjoys a more extensive operation of a market for healthcare than most other areas, given its relative density of provision and relative ease of travel, particularly in Inner London. However, it is still found that outside of particularly large, or specialist hospitals, care is local, and the service areas of those hospital Trusts are themselves relatively small. In fact, the apparent expression of choice at the London scale for hospital care seems less pronounced than it did within Southwark in the prior examination of primary care. Again, this seems to reinforce the importance of distance, a few extra hundred metres to visit a GP surgery that is not merely the closest seems viable to patients, whilst it seems impractical to consider particularly distance hospitals in favour of a more local one for routine hospital admissions. Of course, as has been suggested in the case of specialist hospitals, and in disaggregating service areas by diagnosis categories, it may be that the distance a patient is willing to travel is associated with the severity of the condition at hand.

Undoubtedly, healthcare information has an important role to play in the effectiveness of delivering services, and the exploratory examination of this chapter does little more than whet the appetite in terms of the availability of spatial analysis to answering the kind of spatial questions that will be important in the future provision of care. However, it does

demonstrate the enduring ordering quality of distance in providing services, once again stating that it is not to be overlooked in the likely administrative upheavals to come.

9 Discussion, Conclusions and Prospects

9.1 Key Achievements

This thesis has sought to explore local provision of healthcare with regard to spatial access to services; the key achievements and contributions made by the research in this regard are outlined in this section, with reference to objectives listed in Chapter 1.2.

Much of this thesis hinges on the analysis of a dataset of patient primary care registration for Southwark, and enriching this data constitutes Objective 1. The data provide evidence of privileged access only available through collaboration with Southwark Primary Care Trust, and the techniques utilised to enrich it further are demonstrated in Chapter 2. The techniques used result in a dataset that allows a population-level study of access to healthcare for a densely populated, service-rich, socio-economically heterogeneous urban area. As such the research presented is at a fine spatial scale which is often absent in academic health research. Coupled with this, the novel application of the Onomap classification (Mateos et al, 2011) allows for the study of cultural, ethnic, or linguistic origin of patients in a way that would previously have been impossible using equivalent NHS-sourced data. Understanding patients is crucial to making the appropriate choices when it comes to providing effective healthcare, and Onomap adds a dimension to existing data that is extremely valuable in this respect.

The thesis makes the case for spatial context; local demographics are important to a more holistic understanding of healthcare provision. Exploring the representation of spatial information, as per Objective 2, in Chapter 3 and 4 provides a basis for considering local context. Chapter 4 reviews the ethnic composition and structure of Southwark, across a range of scales, and using a variety of techniques. In a practical sense, Chapter 4, demonstrates a novel approach to visualising the segregation between pairs of ethnic groups using techniques that derive from graph theory. At the same time Chapter 4 counsels that an understanding of segregation in Southwark must be founded in an understanding of the politics of local authority social housing managerialism that historically drove the organisation of different immigrant groups in the borough. The most significant

outcome from Chapter 4 raises an important issue with regard to scale in understanding segregation, it suggests that an effective appreciation of segregation might only be available at a spatial scale below that which is routinely disseminated in Government collected statistics. To some extent, it may be possible to state that segregation in Southwark is not a neighbourhood phenomenon, but rather a street-level or building level phenomenon. This carries implications for how we perceive and encourage social cohesion and assimilation in local communities.

Objectives 3 and 4 are met by Chapters 5 and 6, in which classic normative assumptions are challenged, and a density-based method of service area delineation is introduced. An analysis of the observed patterns of patient registration behaviour in Southwark in Chapter 5 suggests that it is common for patients to trade-off small additional travel distances, or travel times in order to access a GP surgery that is not their nearest. Whilst Chapter 6 in particular demonstrates how patterns of patient registration for particular groups can differ dramatically from what could be expected to be the case given a GP surgery's local community. The univariate analysis that is carried out suggests links between the characteristics of patients and their likelihood of accessing particular GP surgeries.

The culmination of research pertaining to primary care in Southwark is encapsulated in Chapter 7, reflecting Objective 5, which is partially based upon work published by Lewis and Longley (in press). Chapter 7 synthesises Chapters 5 and 6 to provide evidence for associations between patient ethnicity and the ethnicity of GPs at a surgery, and the importance of patient age and length of registration. In Southwark, it is shown that minority ethnic patients, particularly those classified as African or Muslim by Onomap, have a lower likelihood of registering with their nearest GP surgery than patients from the British group, unless the GP surgery in question has a large proportion of ethnic minority GPs. Undoubtedly, understanding patient behaviour with regard to registration with, and potential usage (were such data to become available) of, GP surgeries is integral to providing effective local care.

Finally, Chapter 8 ascertains that some of the key methods used with regard to primary care are transferable to the hospital care context (Objective 6). As such, Chapter 8 highlights the importance of spatial methods in understanding local provision and competition between hospital trusts. This chapter points to the viability of the methods employed in the thesis,

and hints at the scope of future work that could be undertaken using existing healthcare data.

9.2 Wider Implications for NHS Policy

The NHS has been characterised by observers as undergoing a “permanent revolution” in almost every aspect of how it operates. At the same time there is a belief that it is in the interest of public health to base changes and choices in providing healthcare on evidence (Katikireddi et al, 2011), and that many current policy initiatives lack the underlying evidence base through which effectiveness can be ascertained. This thesis has presented a spatial basis for exploring patterns of local provision of healthcare, and it does so against the backdrop of a changing NHS.

A finding with important policy relevance is that there already exists a significant degree of patient choice of GP surgery within the primary care sector. This is evidenced with a case study of the London Borough of Southwark. However, at the moment there is a strong suggestion that geography has an important role to play in mediating access to healthcare – patients are unlikely to travel much beyond local services in order to receive care; they are only likely to trade-off relatively small additional distances in order to register with a GP surgery other than their closest. Up until this point, however, the patterns observed may have been constrained by the NHS’s imposition of a geographical basis to registration – through catchment areas. Initially, the NHS were to abolish catchment areas, removing the explicit geographical constraints to patient choice. However, it has more recently been reported (GP Business, 2011) that in the forthcoming GP Contract the abolition has not gone through, and that instead removal of catchment areas is merely being trialled in a few candidate locations. At the moment, GP surgeries provide a local service which is evidenced in observed registration patterns in Chapter 5, and there is little to suggest that this would change significantly in the short term were geographical barriers to entry to be removed, GP surgeries remain, after all, location based services.

It will be interesting, if possible, to revisit the patterns of patient registration periodically to explore whether the reemphasis of patient choice has a tangible effect on the observed distributions of patients. The suspicion is that evidence of such an effect would be limited: Moon and North (2000) and Corrigan (2005) both highlight that choice has always existed in

NHS primary care, suggesting that the real driver in patient choice may be differentiation in the services that can be provided by GP surgeries. To this end, Chapter 7 suggests that patients value larger GP surgeries, providing evidence that the emergent trend for health centre-style GP facilities that can provide some outpatient treatments may be a legitimate direction for services to go, particularly in areas with a younger population. Coupled with this, the issue of drivers of patient choice deserves revisiting on a wider scale, research in this area tends to be dated, and is relatively sparse anyway. However there are clear advantages to understanding how patients choose and use primary care health services, particularly as the NHS as a whole becomes increasingly primary care focused. In the future such understandings may have important social marketing implications when it comes to targeting interventions at the local level.

The derivation of service areas for hospital trusts in Chapter 8 highlights the potential for further consideration of the importance of choice in the provision of hospital care. Previously, it had been suggested that competition between hospitals was unlikely to occur outside of major urban areas, and that it was only really evident at the boundaries of market areas. Chapter 8 explores the spatial patterning of patients receiving care from hospital trusts in Greater London, a context in which patient choice, and hence provider competition should be readily apparent. However, the results seem to suggest a distinctly local focus to provision of inpatient and outpatient care; hospitals do compete for patients to some extent, but each hospital only tends to compete with a relatively small local set of competitors. Understanding how hospitals compete, and how they can do it effectively will be important to trust managers, particularly as numerous trusts negotiate their transition to Foundation status, or face the prospect of merging with other trusts. Coupled with this is the emergent reality of privately run, “mutual” healthcare trusts, whose presence, and effective participation in the hospital system is as yet not clearly understood.

Finally, the presently vague NHS data policy will be intrinsic to supporting and developing an effective evidence base. Chapter 2 discussed the importance of spatial data infrastructure with regard to this, and suggested that the present policy of joining up locally stored and managed data sources may prove to be inefficient and ineffective at providing researchers with the data they need. Further, the dissolution of a formal, hierarchical geography of care through Strategic Health Authorities and Primary Care Trusts calls into question how future

data will be aggregated, who will be responsible, and how it will be collected and disseminated.

9.3 Future Prospects

Reflections upon this thesis will undoubtedly break ground on a number of important, useful and interesting areas of further study. Rather than attempt to formalise them all however, this section will instead focus on four areas of particular import and interest: web mapping and online dissemination; alternative approaches to density estimation; subjective measures of accessibility; and greater emphasis on mobility.

Impact and dissemination of research findings has become an integral part of research funding of late; outputs of this thesis, particularly those in Chapter 8, could benefit healthcare managers, as well as patients if available in an accessible way. Gibin et al (2009) describe the benefits of using Google Maps “mashups” – the mixing of spatial data from different sources over a common basemap – for profiling and monitoring population characteristics, and targeting health outcomes through local public health service planning. There is enormous scope to provide timely and relevant health data to the public, managers and policy-makers at a local level of spatial resolution. This thesis demonstrates a number of useful elements that would suit a web environment; particularly GP surgery and hospital service areas, as well as small area reporting of health statistics. Mapping these elements would dovetail with the NHS’s goal of making the public more aware of their choices, and present an interface that could create a better informed healthcare system.

In thinking about the approach to density estimation in this thesis: kernel density estimation (KDE), we can acknowledge that the application of a uniform kernel may not reflect the underlying geography of the point pattern being smoothed. The basis for this is that KDE employ a mathematical function (a kernel) which spreads a phenomenon out identically in all directions. The kernel is isotropic – it gives equal weighting to all directions, however there may be cause to suggest that an anisotropic approach is more suitable, in which some directions have more weight than others (Páez, 2004). Assuming isotropy at a local scale may be unrealistic due to natural breaks, such as rivers, or the imposition of man-made objects such as walls, busy roads etc. If the objective is to characterise spatial segregation, as in Reardon and O’Sullivan’s (2004) work, then failing to account for spatial structure in this

way may be misleading. One interesting approach that may offer an innovative re-exploration of some of this work, is network KDE density estimation (Okabe et al, 2009) which constrains density estimation to an existing network infrastructure. Figure 9.1 demonstrates the Southwark population density, from the Southwark Patient Register for 2009, estimated subject to the OS MasterMap Integrated Transport Network using the SANET toolkit (Spatial Analysis on Networks: Okabe and Satoh, 2009) in ArcGIS. Such a technique would also allow the creation of service areas estimated subject to the road network which might provide a more realistic delineation of patient registration.

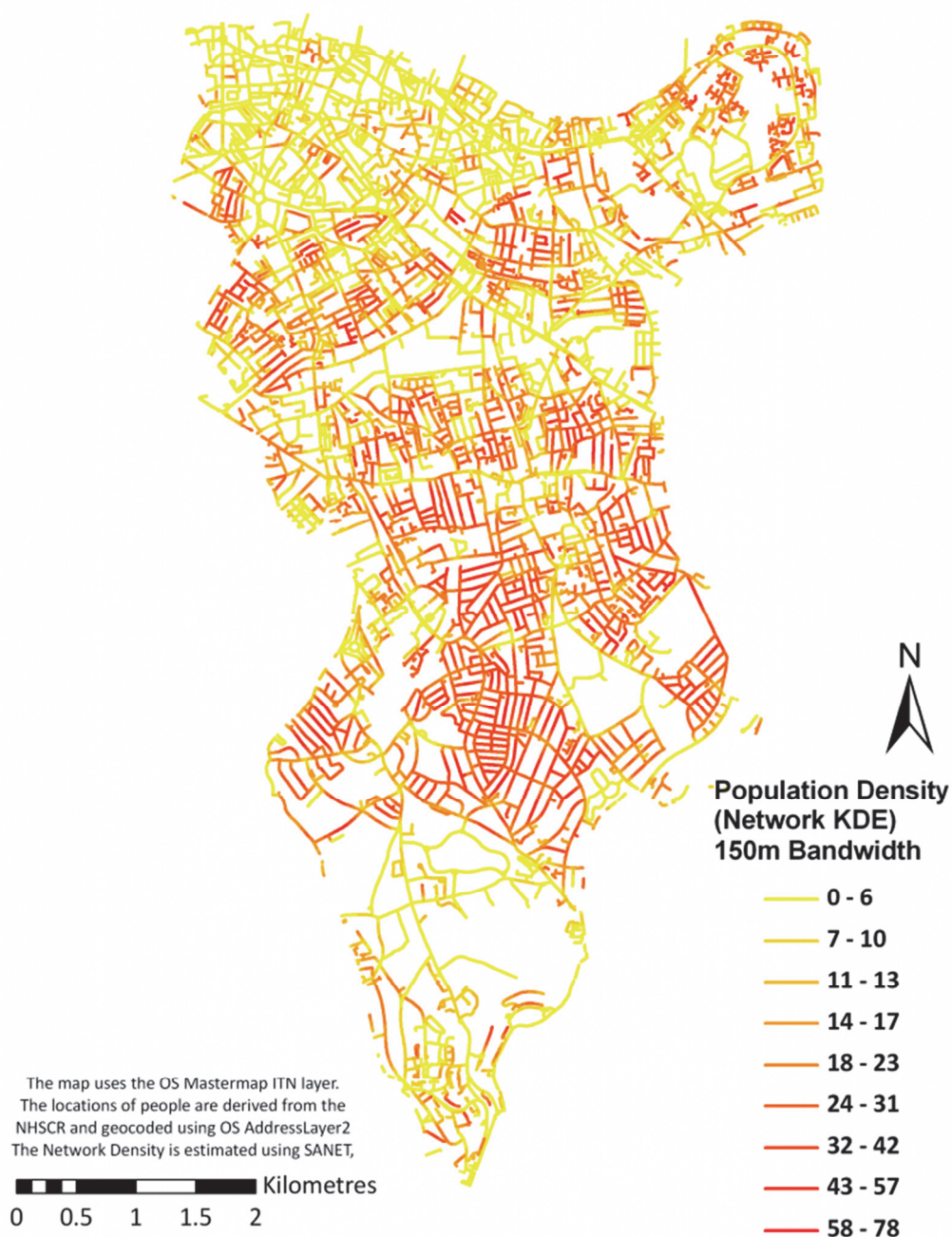


Figure 9.1: Southwark Population Density on the Road Network, 2009.

Using subjective measures of accessibility would involve the use of objectively created measures of access and registration created in this thesis to develop, or implement some measures based on qualitative GIS (see Cope and Elwood, 2009). The conceptualisation of qualitative GIS is that it is a mixed methods approach to doing GIS, which commits to integrating multiple forms of knowledge and findings into spatial description and analysis through GIS. Therefore, this approach would involve working with communities in order to develop a better, and more nuanced understanding of the trends highlighted within this thesis with respect to patient behaviour and choice of primary care services. Feeding back structured qualitative data into a GIS could help us better understand some of the patterns evident in the Southwark Patient Register, in particular it may make for a useful description of “quality” of different services, something that is notably lacking in contemporary NHS data regarding primary care.

Finally, reflecting upon the measurement of accessibility in the thesis, there is scope to think about how the possibility of different patient mobilities (Gatrell, 2011) may affect how different patients access healthcare. Spielman and Yoo (2009) suggest that “individual heterogeneity” is an important consideration in understanding the relationship between environment and health. Linking patients to their health outcomes, or modelling likely circumstance given their demographics, could help distinguish further differences between population groups by their particular mobility with regard to accessing a GP surgery.

9.4 Reflections on the Research Themes

The introduction to this thesis began by sketching out the key, cross-cutting themes that would shape and hopefully define the contribution made by the research. These themes pointed to broader disciplinary intersections of health and medical geography; to confront them on an ‘as-and-when’ basis without some prior engagement or acknowledgement seemed to be as foolish as failing to acknowledge them in the final, summary discussion. Thus, the first recourse in reflecting back upon this thesis as a whole is to consider the trajectory that these themes took as both frameworks and outcomes of the research.

9.4.1 Health and Medical Geography

In many ways the health and medical geography prescribed by Kearns and Moon (2002), and latterly in the “companion to health and medical geography” edited by Brown, Moon

and McLafferty (2009), acts as a framework for this thesis. The articulation of a reformed health and medical geography has helped push the discipline forward on a number of fronts, however the core area relevant to this thesis in which research has failed to be forthcoming is in creating a progressive understanding of how to do health services research.

In some respects health services research is well catered for, Cromley and McLafferty (2002) comprehensively detail the application of GIS in public health, paying particular attention to health services. Indeed, GIS has much to offer an expanded understanding of health services research, some of which is covered in 9.4.2. However, the application of a new technology cannot on its own be considered a progression in approaches to health services research, in some ways GIScience has been taken 'as is' in framing 'health GIS', and there has been limited transference of the "novelty" of health and medical geography.

This was not something that was apparent at the onset of the PhD process, and it was something that was made apparent more by absence than an actual discussion as to the place of health services research within health and medical geography. Lohr and Steinwachs (2002) seemed to sense this when they set about redefining the field of health services research for the journal of the same name; they were quick to acknowledge that "in some respects, the definition of this field has not changed since the early days" (p. 16). Lohr and Steinwachs note that as early as the 1970s health services was described as "a field that develops methods for improving access to care" (2002 p. 16), however their amendments see it including "personal behavio[u]rs" and "social factors" which are now recognised as having important influences on the need for services.

In a sense, largely spatial descriptions of access, such as those examined in Chapter 3, might be considered to be somewhat dated within health and medical geography. Barnett and Copeland (2010) suggest that this kind of health services research privileged four themes: "geographical bases of service organisation, locational variations in the provision of health services, resource allocation in relation to need, and variations in service use" (p.498) and that such foci were influenced by "logical positivism". However, this thesis too undoubtedly privileges those same themes, as advocated by the use of geographic information science and GIS. On top of this, the overriding sentiment of the thesis is rather "welfarist" in tone which is again reflected by this earlier body of work in health services.

There is much need for a re-evaluation of health services research given the changing geography and reforms to healthcare in the UK, and internationally. There are reasons to be optimistic however, the forthcoming World Health Organisation “World Health Report 2012” promises a justification that “research is essential to improve health outcomes” (WHO, 2011: No page number).

9.4.2 GIS, GISci and Spatially Integrated Social Science

Highlighting spatially integrated social science (Goodchild and Janelle, 2004) in the context of this thesis was an invitation to reflect on two important factors: the legitimacy of location in linking approaches from different disciplines to further the analysis at hand; and the difficulty with regard to thinking spatially that is entailed by doing spatial research in any discipline.

On the first point there will always be competing understandings of spatial concepts, location is not strictly interpretable as place, whilst administrative zones may not necessarily represent neighbourhoods. Recently, research has emphasised the importance of place through its uniqueness, and has unpicked the importance of narrative (“Stories so far”: Massey, 2005), multiplicity (“folding and unfolding”: Doel, 1999), relations (“relational space”: Murdoch, 2005), and experience (Kearns and Collins, 2010; Moon, 1990) in defining place. That any representation of place is partial is an inevitable conclusion, however one of the benefits of this thesis is that the methods and techniques used are transparent, open to scrutiny and reproducible; as such it is possible to gauge the sensitivity of outputs based upon their inputs.

Further, location suggests a fixity that may not be valid. The context that can be given to the data itself is relatively limited, and thus a service user is understood purely in terms of their (possibly historic) residential location – the address they gave when they registered with a GP surgery, for instance. However, this may only effectively represent a “night-time” population (Martin et al, 2009), and the patterning of trips to services may vary if users are not making them from their given residential address, inherently changing the pattern of spatial equity and usage of the system. Similarly, access to services may vary with the concessions they make to open earlier or close later, or hold weekend surgeries, as this increases the potential to access a service for particular groups. However, the approaches in this thesis do not consider these variables, mostly owing to the difficulty of obtaining the

requisite data, and applying it within a spatio-temporal framework; Weber and Kwan (2002) emphasise the influence of facility opening hours on individual access. Further, Neutens et al (2008) call into question the relevance of individual accessibility in some situations, suggesting that understanding the potential of multiple participants might be more applicable, necessitating a measure of "joint accessibility"; in this thesis the accessibility of young people is dependent on their parents which might influence decisions with regard to accessing a healthcare service, however in Chapter 7 they are simply excluded from consideration.

Spatial thinking is an important element of spatially integrated social science, and indeed a rhetorical backbone of NHS policy. Moon and Brown (2000) have emphasised the importance of spatial signifiers in NHS policy, and this thesis is, at points, a practical examination of how spatial rhetoric translates into an observed reality. The thesis seeks to establish whether the articulation of local provision, and in particular, patient choice, as heralded by Central Government is present 'on the ground'. The author's experience of working in, and visiting, Primary Care Trusts suggests that there may be a general failure within PCTs to think of data as a strategic and tactical resource in the way that the private sector does. Under the current structure there is often limited capacity to effectively engage in spatial thinking and analysis at the local level; however those who do will derive a sizable comparative advantage.

9.4.3 Equity and Access to Healthcare

As suggested in Chapter 1, and as was evident in subsequent empirical chapters, the thesis avoids confronting equity head on. To do so in the context of this thesis would require equity to take an analytical form, most likely founded in a partial measurement of "need" for healthcare, when in reality there is limited scope to do this. Instead, equity is considered simply as a subjective outcome of healthcare systems; an analysis of variation in access provides the context for the suggestion of comparative spatial inequities between different groups. Thus the contribution relates not strictly to an all-encompassing form of equity, but to one seen through the eyes of a geographer, and interpreted through a discourse of welfare geography and social justice. Such considerations rely on a critical engagement with policy, as well as the formal representations made by GIS.

The most significant consideration related to equity and access in this thesis is in the difference between the potential to access healthcare services, and the observed patterns of access. In Chapter 3, a number of “potential” style measures of access and spatial equity are considered; they are referred to as potential measures because, in theory, the measures capture the spatial variation in an individual’s opportunity to access a healthcare service. However, in Chapter 5, the idea of “revealed accessibility” is considered; these are the actual patterns of registration, which demonstrate that a high potential access does not always translate into a similarly high observed access. In fact, older people, and people from particular minority backgrounds seemed to have, on average, worse accessibility characteristics relative to other groups than could be expected. It was for this reason that the thesis moved in the direction of unpicking registration patterns and behaviours in Chapter 7, rather than rehashing increasingly complicated potential models.

There are three other relevant aspects to consider when considering access and equity in the context of this thesis. Firstly, and by analogue to the earlier consideration of location and place, there is no appreciation of the difference in the thesis between movement, or flow between patient and GP surgery, and “mobility” (Gatrell, 2011). Generally, people are assumed to have a consistent ability to travel to a service regardless of circumstance; however this is unlikely to be true, and a consideration of differences in individual mobility may further emphasise spatial variation in access to healthcare services. Secondly, Hawthorne and Kwan (2011) introduce the idea that distances can vary due to subjective considerations of the quality of services and of alternatives, particularly in low-income communities. Subjective variations in distance to GP surgeries in Southwark may be important in further explaining the apparent patterns of patient registration behaviour.

Finally, Gatrell (2011) highlights the mobility of information in healthcare choices, particularly the influence of social network effects; it is highly possible that patterns of registration with some GP surgeries, particularly amongst minority groups, are influenced by the recommendations and guidance of friends, family, colleagues, and neighbours. The NHS has advocated for greater access to information as a key component in broadening the basis for choice in healthcare (DH, 2010), but the extent to which available information about healthcare choices is utilised by patients is unclear. Coulter (2010) suggests that patients tend to rely on informal information sources, with less than 10% of patients using official sites; Coulter even goes so far as to suggest that GPs themselves distrust the information

available on quality and performance on official NHS sites. The NHS Choices website offers patients the possibility of reviewing their service providers by adding comments to the GP surgery or hospital listings, Lagu and Lindenauer (2010) align this with attempts to increase transparency in healthcare. However, it is as yet unclear as to how useful these ratings will prove, nonetheless they could be an interesting input into advancing the consideration of access in healthcare.

9.5 Closing Statement

This thesis has explored spatial access and the local provision of healthcare services, highlighting the enduring relevance and importance of geography. Its contribution represents a timely benchmark, or baseline, understanding of the existing complexity of patterns, and behaviour, associated with accessing primary care in particular, but also hospital care. To all intents and purposes, the NHS is on the cusp of radical change, both directly instituted through the imposition of a new health and social care bill, and indirectly as population demographics change, placing new demands on existing services. Much of the work presented in this thesis is novel, and showcases the importance of spatial thinking and analysis in healthcare. Inevitably, further work will be done on the topics covered in this thesis, it is too important for this not to be the case, and on that basis it is hoped that the fruits of this thesis find their way into future reckoning.

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Appendix: Published Outputs from PhD

A1: Peer Reviewed Publication (Attached)

Lewis D., and Longley P. In Press. Patterns of Patient Registration with Primary Healthcare in the UK National Health Service. *Annals of the Association of American Geographers*.

A2: Working Paper

Lewis D., Mateos P., and Longley P. 2009. Choice and Composition of General Practice Patient Registers. CASA Working Paper 150. Available at: <http://www.bartlett.ucl.ac.uk/casa/publications/working-paper-150> last accessed: 23/11/11

A3: Peer Reviewed Conference Papers

Lewis D. 2010. An Assessment of three Service Area Models for Healthcare Service Analysis. In Haklay M., Morley J., and Rahemtulle H. (eds.) *Proceedings of the GIS Research UK 18th Annual Conference*. UCL, 14th-16th April. 277-284

Lewis D., Mateos P., Gibin M., and Longley P. 2009. GP Catchments and the Characteristics of Patients: a 'Postcode Lottery'? In *Proceedings of the GIS Research UK 17th Annual Conference*, Durham 1st - 3rd April 2009

Patterns of patient registration with primary healthcare in the UK National Health Service

Daniel J. Lewis - Department of Geography, Queen Mary, University of London, Mile End Road, London E1 4NS, UK

Paul A. Longley - Department of Geography, University College London, Pearson Building, Gower Street, London WC1E 6BT, UK

Abstract

The UK National Health Service (NHS) is a long established universal provider of health care. Most primary care is delivered by General Practitioner (GP) run health centers (surgeries) which, subject to proposed policy changes, are increasingly central to the welfare geographies of the NHS. This paper develops an analysis of a unique and hitherto under-exploited dataset, comparing the observed pattern of patient registrations at GP surgeries with an optimum geographic pattern in the London Borough of Southwark. In addition to evaluation of the level of geographic order that arises in a locally-administered, centralized system of health care provision, we also use a new and innovative ethnicity classification tool to assess the ethnic dimension to deviations from the normative arrangement. These results are considered in the light of current and recent initiatives regarding patient choice in the United Kingdom.

Keywords:

Ethnicity classification; National Health Service; patient choice; primary care

1. Introduction: Reforms in UK primary care provision in an international context

Reform of primary healthcare is often viewed as politically necessary in many healthcare systems, as in the Obama administration's initiatives to extend eligibility and coverage, but also more widely in systems affected by neoliberal government agendas for transparency, and cost savings in public finance. On-going debate in the UK National Health Service (NHS) centers on the role of General Practitioners

(GPs) not only as providers of primary care, but also as procurers of secondary (hospital) care. The organization and management of local delivery of healthcare through the system of (privately owned) GP surgeries, whose staff are usually the first point of patient contact in the UK system, is key to proposed healthcare reforms. Prospective patients have the right to register with a single GP surgery and receive healthcare that is free at point of delivery. Reforms envisage the devolution of budgets behind commissioning of services to GP-led consortia, and competition between public and private providers in providing care in a more market-oriented way, akin to the operation of Health Maintenance Organizations (HMOs) in the United States. Central government recommendations (DH, 2010) to give patients both a wider and freer choice in accessing healthcare, if implemented, will have profound geographic implications on primary care, with similarly far-reaching consequences for hospital care.

The NHS health improvement agenda is increasingly primary-care led as well as primary care focused (Moon and North, 2000; DH, 2005), and is seen as providing better value for money than relying on expensive hospital services. Concurrently, the articulation of choice has shifted from a doctor-patient dialogue to one more firmly centered on the rights of the patient (DH, 2006; 2008a). Reforms set out in the radical 2010 white paper "Equity and excellence: liberating the NHS" have stated that any patient should be able to choose or change their GP surgery without being "limited to one that is nearest to your home" (DH, 2010).

This policy shift significantly loosens the geographic basis to organization of NHS services, which has always hitherto advocated that patients should register with geographically proximate GP surgeries, in the interests of efficient and effective provision of primary healthcare. Catchment areas, initially ad hoc, later formalized (Martin and Williams, 1991), although never fully implemented in practice, formed a basis for service delivery. However, in densely populated urban areas, NHS concerns have focused upon the needs of the elderly, disabled, and young families for whom GP surgeries should, for example, be "within walking distance for mothers with

prams" (Ministry of Health, 1962: source Sumner, 1971). Morrill, Earickson and Rees (1970) have noted that in U.S. city centers, where several health centres might serve a small densely populated area, patients are less likely to use their nearest physician. This tradeoff in choice and accessibility by patients will become an increasingly interesting facet of provision of primary healthcare in the UK should stated NHS reform proceed. Given the centrality of this premise to provision, there is something of a dearth of literature on the geographies of patient registration in UK cities (but see, inter alia, Wilkin, Metcalfe and Leavey, 1987; Joseph and Phillips, 1984; Knox, 1978).

This paper uses a case study of the London Borough of Southwark to consider how patient registration behaviour deviates from a normative geographic arrangement. A complete listing of patient registration provided by Southwark Primary Care Trust (PCT) at the patient level represents a privileged view of patient – GP surgery interaction, wherein, given the very varied ethnic composition of the study area, we focus upon indicators of patient ethnicity to analyze variation. We provide a contemporary insight into the pattern of choice of GP surgery by patients, in which the behaviors manifest in existing spatial patterns of registration add weight to the suggestion that choosing a GP surgery is not an innovation to be imposed, but a pre-existing condition of primary care in the urban context.

2. Equity and Choice of GP in the NHS

The NHS has a duty to provide a universal service to the UK population, underpinned by the notion of equity, that is, "a just distribution justly arrived at" (Harvey, 1973: 16) defined for healthcare by Asthana and Gibson as "equal opportunities of access to healthcare for equal needs" (2008:4). We focus on the spatial equity of access to the healthcare system, namely "the question of who benefits and why in the provision of urban services and facilities" (Talen and Anselin, 1998: 596). The tradeoffs between promoting choice and equity are numerous and contested, and we do not propose to cover them here, beyond the obvious apparent view of Dixon and Le Grand that:

“[g]iving choice to individuals and groups who previously had none... will extend to all a privilege that was previously confined to those who could afford private healthcare.” (2006: 166)

Corrigan (2005) contends that choice has been a factor in primary care ever since the creation of the NHS in 1948, consistent with the stated intention of ensuring equal quality of care wherever it is sought (see also: Moon and North, 2000).

However, the uniform nature of GP services, and lack of information on differences where they do exist, ensured that patient choice of GP surgery was principally driven by location. Exworthy and Peckham (2006) and Greener (2007) note that it is unusual for patients to be willing to travel beyond local services, while a series of studies of the NHS in the late 1980s and 1990s similarly identify location as key to choice of GP surgery (Gandhi et al, 1996; Billingham and Whitfield, 1993; Salisbury 1989). In the urban context, however, available local services can include numerous GP surgeries, in the case of Southwark, for example, many catchment areas defined by GP surgeries overlap each other; overlap the artificial boundaries of the borough; may not correspond to the areas where many of their patients live; or may simply be so extensive as to effectively stipulate no catchment at all.

A patient living within a catchment area can expect to be provided with GP services, including home visits if required, assuming they are registered to that GP surgery. Although, if the surgery is operating at capacity, the list may be closed to new registrants, irrespective of their residential locations, and the GPs will not be obliged to provide healthcare services to additional patients. The basis for defining a catchment area comes from the need to regulate the workload of the GPs at any given surgery, and in practice catchments are agreed by negotiation between the GP and the relevant local NHS body. The NHS Constitution (2009) deems registration with a local NHS GP surgery a “right”, but managing catchment areas and service quality is challenging, with a recent NHS survey reporting that “members of some black and ethnic minority groups, commuters, and people living in more deprived areas are more likely to report dissatisfaction with services. These groups want

greater control of how and when they access primary care” (DH, 2008b). Reforms, in their present state, would seek to abolish catchment areas.

3. Framing Evidence for Choice in Southwark

The Borough of Southwark (Figure 1A) is an Inner London local authority some 30 km² in extent, and is home to almost 300,000 people. It is ranked the twenty-fifth (of 326) most deprived local authority in England (Index of Multiple Deprivation 2010: an index of hardship¹). Over 30 percent of Southwark’s residents are members of ethnic minorities (Figure 1B); and the local authority is landlord to the largest stock of social housing in London (Southwark Council, 2010). However, affluent enclaves are also to be found in Southwark, particularly along the River Thames, and to the south. There are forty-seven GP surgeries in Southwark, providing employment for c.200 general practitioners.

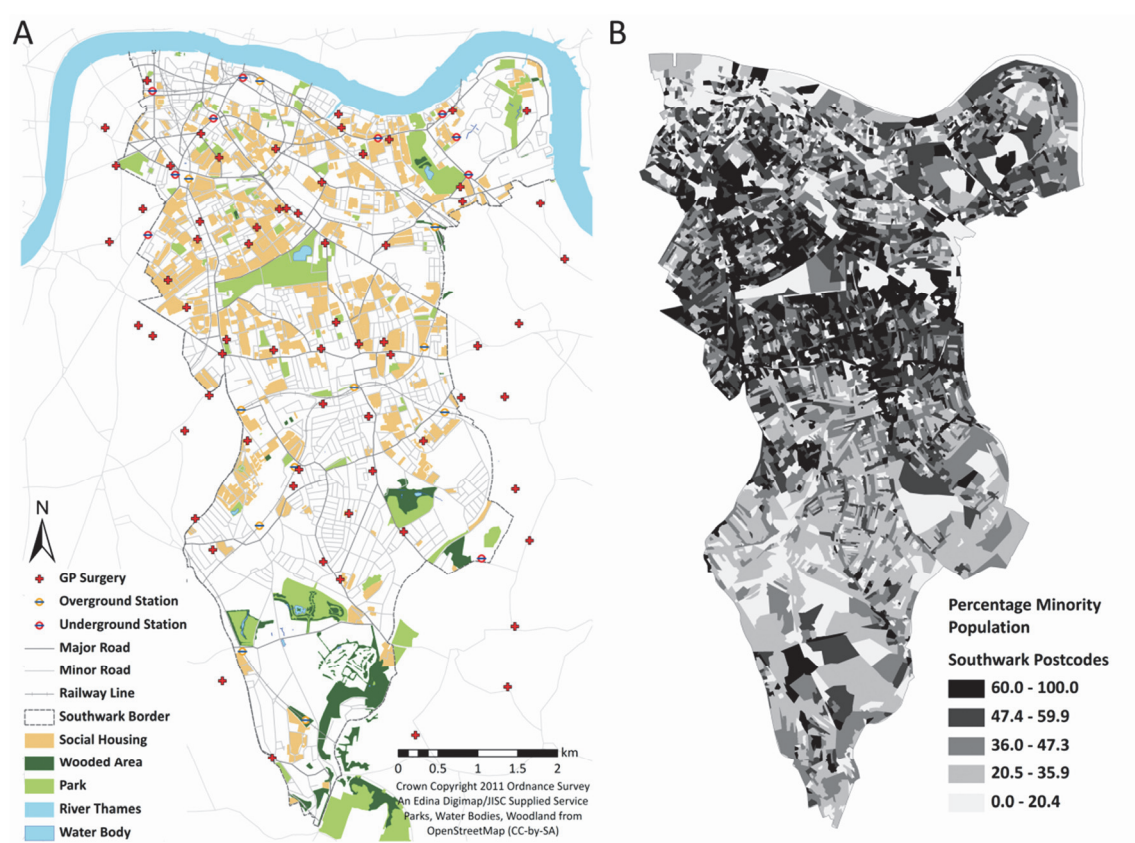


Figure 1: Location map of Southwark (A) and proportions of ethnic minority patients by postcode (B).

Southwark patient data were drawn from the May 2009 National Health Service Central Register (NHSCR), which records all patient registrations with a GP surgery in the UK. The extract identifies the full names and addresses of every Southwark resident registered with any GP surgery. These unique patient data were obtained following successful application for ethical approval to the appropriate NHS research ethics committee. Difficulties in handling patient residential mobility means that the number of records on the NHSCR is likely to be an over-estimate of the actual size of GP lists. The study population for Southwark comprises c. 325,000 people using forty-seven GP surgeries in Southwark and 127 GP surgeries in its environs.

The motivation for this research is to investigate the deviations between the observed and normative patterns of registration, particularly with respect to patient and GP ethnicity. We do this by considering the network distance between each patient and their GP of registration, characterizing patients as travelling an additional distance if they use a GP surgery that is further away than their nearest, assumed to be the normative choice. Each GP surgery and patient residence is address georeferenced using Ordnance Survey MasterMap Address Layer 2 (a database of residential and commercial building locations) and distances are computed on the Ordnance Survey MasterMap Integrated Transport Network (ITN).

The classification of ethnicity is often inherently subjective and error prone in medical records, and our chosen approach was to classify patients using the Onomap classification which indicates the likely cultural, ethnic or linguistic origin of each individual patient based upon their forename and surname pairings (Mateos, Longley and O'Sullivan, 2011; Mateos, Webber and Longley, 2007; Petersen et al, 2011). This adds considerable value and consistency to the NHSCR birthplace records which are error prone and may fail to identify second generation members of ethnic groups. Coding the ethnicity of individual patients makes it possible for the first time to undertake a non-ecological study; ethnic variation in GP registration is an important, but under-researched facet of primary care provision, and coding patient ethnicity by their name presents an innovative approach to resolving this.

Lakha, Gorman and Mateos (2010), in a validation study based on Scottish public health data, suggest that "Onomap offers an effective methodology for identifying population groups in both health-related and educational datasets, categorizing populations into a variety of ethnic groups" (p.1).

The ethnicity-based segmentation of Southwark GP registration data makes it possible to see which groups are more, and which are less, likely to register with GP surgeries which are close to their residence. These behaviours are likely influenced by numerous factors (Hays, Kearns and Moran , 1990; Joseph and Phillips, 1984) reflecting differences in age (Ahmad, Kernohan and Baker , 1991; Hopkins et al, 1967), sex (Salisbury, 1989), social class (Goddard and Smith, 2001), wealth (Knox and Pacione, 1980) and other locational factors (Bullen, Moon and Jones, 1996). As such, observed behaviours may reflect clear cut patient preferences, but equally may simply reveal the effect of patients conforming to, or constrained by, other aspects of the system. Hawthorne and Kwan (2011) have suggested that a qualitative understanding of the humanistic factors regarding access to healthcare are important, because patients can impose an added perceived distance when faced with low-quality health provision. Knowledge of the local patterns of patient registration could be an important precursor to uncovering these subjective drivers to choice, with evidence for demographic variations providing a basis for qualitative enquiry.

4. Patterns of Registration with GP Surgeries in Southwark

The proximity rank of a patient's GP surgery of registration offers the possibility of a baseline measure of spatial efficiency, in which patients not using their nearest GP surgery (assuming unconstrained capacities) introduce spatial inefficiencies. The cumulative distribution of patient proximity ranks for registration with Southwark GP surgeries is shown in Figure 2.

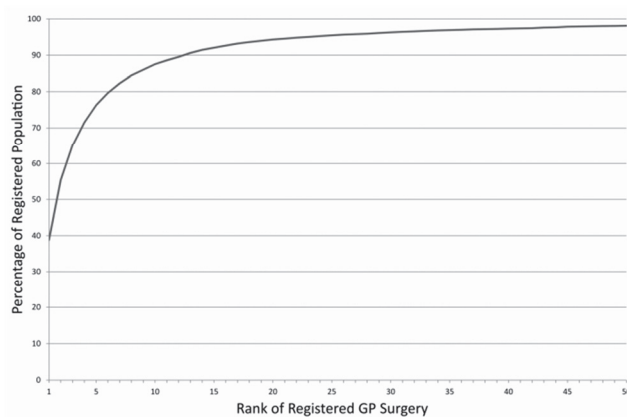


Figure 2: Cumulative percentage of GP surgery usage by rank.

Approximately 40 percent of Southwark residents use their nearest GP surgery, and 80 percent of residents use one of their nearest 6 GP surgeries. This suggests that a relatively large number of patients are either willing to, or required to, make small trade-offs in accessibility against other considerations in registering with a particular GP surgery. Table 1 demonstrates the geographic inefficiencies consequent upon patients not using their nearest GP surgery, measured as additional distance travelled.

Rank Order	No. of Patients	Additional total distance travelled (km)	Additional mean distance travelled (m)	Additional median distance travelled (m)
1 (40%)	128,137	0	0	0
2	53,494	11,226	210	151
3 (66%)	32,828	11,546	352	293
4	20,529	10,269	500	440
5	15,412	8,721	566	550
6 (80%)	11,205	7,659	684	641
7	8,547	6,544	766	749
8	6,476	5,463	844	799
9	5,608	6,790	1,211	975
10	4,492	4,787	1,066	953
11	3,152	3,454	1,096	1,004
12 (90%)	3,126	3,897	1,247	1,119
≥ 13	32,258	75,389	2,337	1,865

Table 2: Additional distance travelled to GP surgery by rank

Roughly 197,000 patients each travel an average additional 790 m (around ten minutes walking time) to use a GP surgery other than their nearest, with the median additional distance approximately 479 m. The preponderance of short additional distances provides good evidence for patients exercising choice in some form. The geography of additional distance travelled is not itself geographically random: Figure 3 presents two smoothed representations of the proportion of people using their nearest GP surgery.

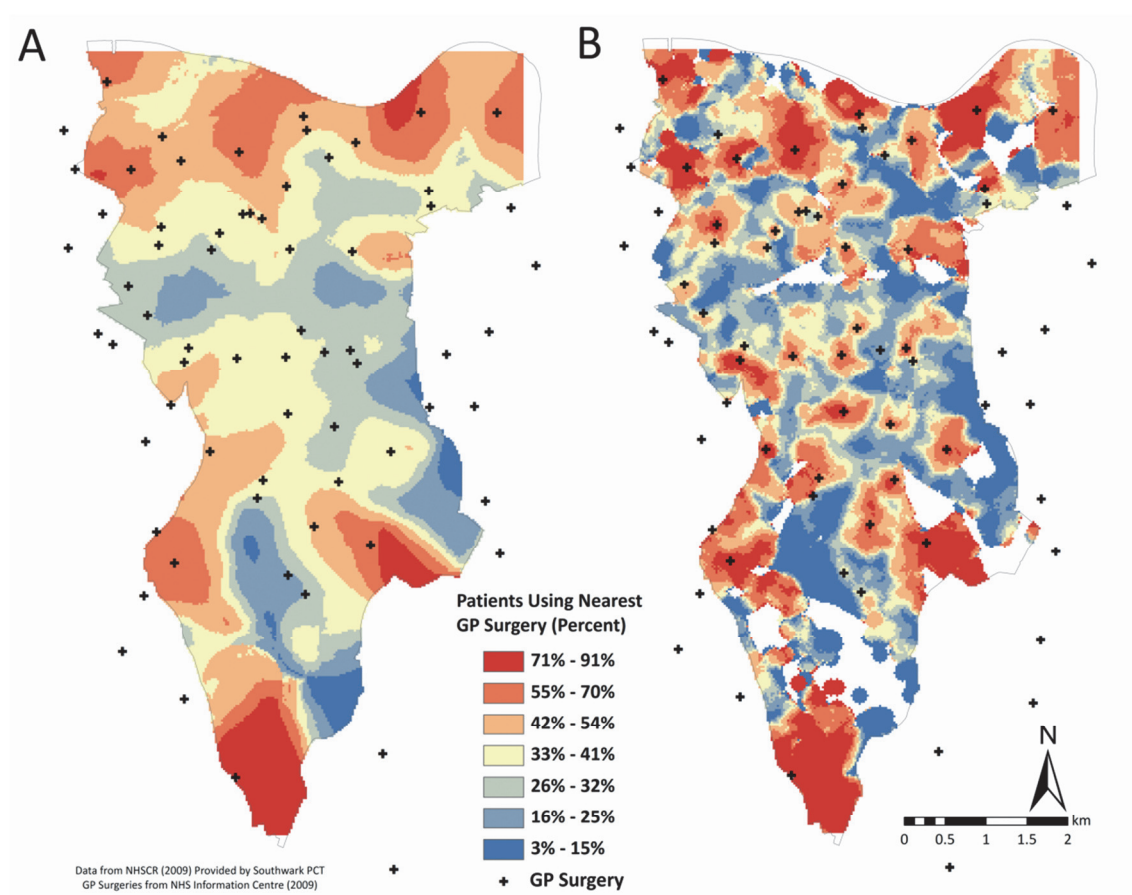


Figure 3: Percentage of patients using their nearest GP surgery. Gaussian kernel smoothing for A) 500 m and B) 100 m.

Figure 3A makes apparent that patients living in areas that lie at borough boundaries (such as the River Thames to the north) or in areas which have a lower density of GP surgeries (such as the south) are more likely to use their nearest GP surgery. At a finer level of granularity, site specific effects become more apparent, with the lowest percentages of patients travelling extra distances in the immediate vicinities of GP surgeries. In the more service rich areas, the islands of higher registration

surrounding each surgery are less intense, with smaller spatial extent than the less service rich areas. However, the nature of these distance decay effects is not identical across the borough as a whole, suggesting that there may be additional factors behind the observed pattern of patient registration behaviours.

<i>Patient Ethnicity</i>	No. of patients	Mean distance to nearest GP (m)	Mean distance to registered GP (m)	Median distance to nearest GP (m)	Median distance to registered GP (m)
African	35,091	489.2	1138.7 (2.3)	467.3	770.1 (1.6)
British	166,058	515.6	979.0 (1.9)	491.8	773.8 (1.6)
E. Asian	9,451	513.3	1001.2 (2.0)	492.5	720.3 (1.5)
E. European	7,182	505.1	912.2 (1.8)	489.3	698.7 (1.4)
European	45,944	510.4	948.6 (1.9)	490.5	736.2 (1.5)
Hispanic	11,470	480.4	852.9 (1.8)	465.3	688.8 (1.5)
Muslim	31,263	484.5	958.5 (2.0)	464.0	737.9 (1.6)
S. Asian	6,012	542.6	1075.7 (2.0)	504.8	736.5 (1.5)
Other	12,793	501.8	973.7 (1.9)	485.0	723.7 (1.5)

Table 3: Distance to nearest GP surgery and GP surgery of registration by ethnic group in Southwark (Ratio Registered:Nearest)

Southwark's multi-ethnic character provides the motivation for investigating variability in additional distances travelled. Table 2 shows the mean and median additional distances travelled by patients of different ethnic groups, classified using the Onomap² system. It is apparent that African patients travel further on average to use a GP surgery than any other group, although the median distances travelled by all ethnic groups are broadly similar. A Chi-squared test (following Hays, Kearns and Moran, 1990: $\chi^2 = 2504$) of whether patients of different ethnicities exhibit similar registration behaviours with respect to the rank of the GP surgery they use shows significant difference between groups at the greater than 1 percent level. Differences in registration patterns are most apparent amongst the African group within which only 35 percent of patients use their nearest GP surgery (compared to 40 percent for the population as a whole). Conversely, the Eastern European, European, Hispanic

and East and South Asian groups show a more marked tendency to use their nearest GP surgery (44, 41, 43, 43 and 45 percent respectively).

This pattern can be formally tested with a logit model in which the likelihood of a patient registering with their nearest GP surgery is related to demographic characteristics (age, sex, ethnicity), distance to their nearest surgery, the characteristics of provision at the nearest surgery (the number of full-time GPs, and their ethnicity), and an estimate of the number of competing destinations available to the patient. The idea of competing destinations stems from Fotheringham's (1983) work, however, he initially uses the concept in the formulation of spatial interaction models, whereas it is used here as an indicator of available choices. In this way, as the number of possible destinations (GP surgeries) varies for any given patient, the likelihood of registration with the nearest GP surgery can also vary.

In the model, a patient's distance to the nearest GP surgery is defined by the road network distance from the patient's residence. The patient's age and sex is extracted from the patient register and the ethnicity is coded using Onomap, as is each GP's ethnicity. The number of full time GPs per surgery is calculated by taking the number of registered GPs and subtracting a value of 0.5 for each reported part-time GP, which was considered to best represent a patient's impression of the number of GPs at a practice. Further, the proportion of GPs in each GP surgery belonging to an ethnic minority is calculated with reference to the Onomap derived ethnicity of each GP. Finally, the choice set of competing destinations (local GP surgeries) for each patient is calculated by estimating a service area for each of Southwark's GP surgeries based on the observed distribution of patients that are registered with it. The number of service areas that a patient falls within provides a measure of that patient's local opportunity to access a GP surgery. Service areas are created using Gibin, Longley and Atkinson's (2007) method of enclosing a given percentage of the density distribution of patients registered with a GP surgery. The procedure for creating a service area follows:

- 1) Estimate the continuous density surface of the pattern of patient registrations with a GP surgery using kernel density estimation (KDE). This has many desirable properties (de Smith, Goodchild and Longley, 2009) including, in the current application, the maintenance of confidentiality of individual patient records.
- 2) Each cell in the resultant raster has a volume, which can be expressed as a proportion of the whole raster.
- 3) The raster cells are sorted from high to low volume. Cells are then recoded to value 1 up until the desired cumulative percentage of volume (Shortt et al (2005) note that 75 percent is popular). The remaining cells are coded to zero.
- 4) The raster cells are resorted into their original order, and a percentage volume contour (PVC) is drawn to bound the extent of the cells coded 1 in the binary raster. This may create several distinct polygons if the service area created is multinucleated.

Following Shortt et al (2005) the 75 percent PVCs were calculated and taken to characterize a principal service area for each Southwark GP surgery. As the service areas reflect the pattern of patient registration, rather than an arbitrary distance or potential statistic, they can be thought of as a spatial representation of the patient community using a GP surgery. As such, any patient that falls within a service area can be considered as likely to have local neighbors who use the service, designating that GP surgery as lying within the choice set of accessible GP surgery choices for that patient. Patients that fall within more than one service area thus have more scope to exercise choice of GP surgery. The data set is only complete for Southwark, meaning that service areas are not calculated for non-Southwark GP surgeries: the use of the 75 percent PVC generally mitigates edge effects, in view of the strong geographical basis for registration and the resultant tightly defined service areas. The overlaps due to congruent service areas are shown in figure 4.

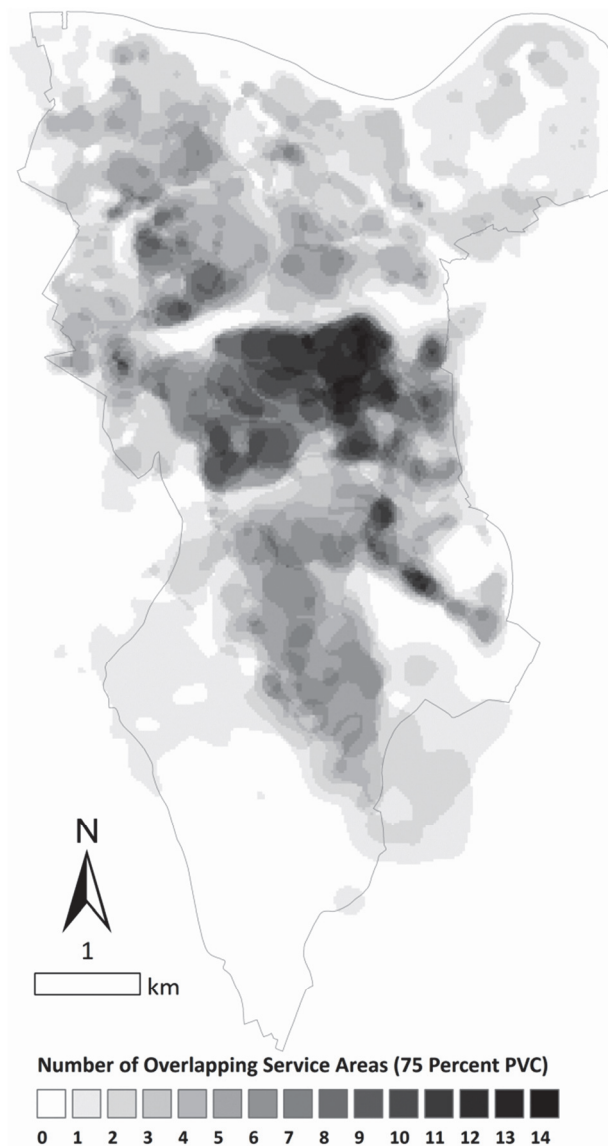


Figure 4: Overlapping service areas in Southwark, derived from the 75 percent PVC for each GP surgery.

Some characteristics of the service areas are shown in Figure 5: the clustering of Muslim and African patients with respect to GP surgery locations is shown in figure 5A, in which South Asian patients are the least well served. The complexity of this relationship is demonstrated in figure 5B which shows the cumulative proportion of patients in each group that fall within the principal service area of their chosen GP surgery. Muslim and African patients are more likely to reside within the principal service area of their chosen GP surgery than their South Asian or white British counterparts, but this only becomes evident when the number of congruent service

areas is very high (>10), below this African and Muslim patient are considerably less likely to reside within the service area of their GP surgery of registration.

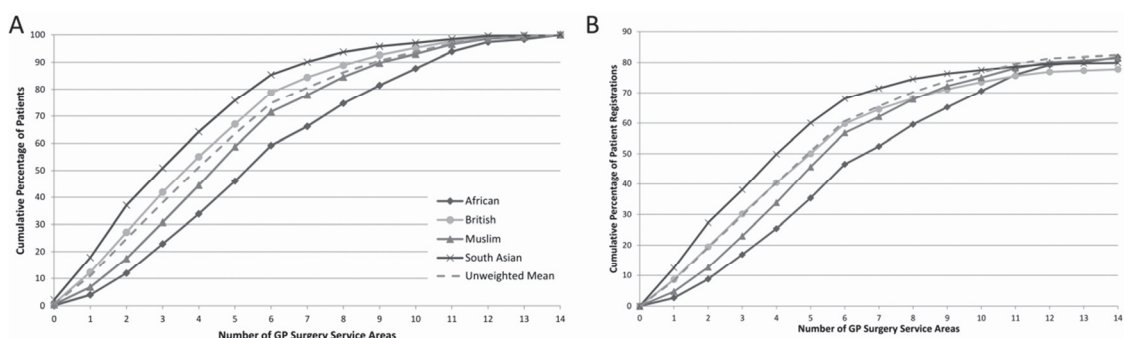


Figure 5: Cumulative proportions: (A) of patients resident within the principal service areas of any GP surgery; and (B) of principal service area residents who are registered with a GP serving the area. Both differentiated according to ethnic groups African, Muslim, British and South Asian.

Table 3 documents a model of patient registration behaviours with respect to their nearest GP surgery, calculated for all patients, excluding patients under sixteen years old whose registrations are constrained by parental registrations. In general, the further away a patient lives from their nearest GP surgery, the less likely they are to use it, similarly the greater the number of service areas belonging to other GP surgeries that a patient's residence falls within, the less likely they are to use their nearest GP surgery. This supports evidence of patients making small distance-based trade-offs in accessing a local GP surgery that may not necessarily be the nearest. However, the larger the nearest GP surgery (in terms of number of GPs) the more likely patients are to use it, providing evidence for the growing utility and attractiveness of consolidated health-centers over more traditional surgeries staffed by only one or two GPs. In terms of differentiation by ethnicity, the modelled results are to be expected: African and Muslim patients are less likely to use their nearest GP surgery than British patients, and vice versa for East Asian, European and Hispanic patients at the 1 percent level of significance and South Asian patients at the 5 percent level. The ethnicity of the GPs at each surgery is also an important factor: as the proportion of ethnic minority GPs (African, Muslim, East and South Asian, and

Other) at the nearest GP surgery increases, the likelihood of a patient using that surgery decreases. However, this result is not consistent over all ethnic groups, there is an interaction effect that suggests that as the percentage of minority GPs at the nearest GP surgery increases, the likelihood that a non-British patient will use their nearest GP surgery increases comparative to the British group. This is particularly true for African and Muslim patients, as well as Hispanic, Unclassified and Eastern European patients, although there is no difference between British and East Asian groups, whilst the relationship is only significant at the 10 percent level for the European and South Asian groups. This suggests that the ethnicity of GPs at particular surgeries can play a role in patient registration behaviours, particular amongst African and Muslim patients.

<i>Variable</i>	Coefficient	Std. Error	z	P> z
Distance to Nearest GP Surgery (km)	-1.680	0.01890	-88.87	0.000
Number of Accessible GP Surgeries	-0.2013	0.002841	-70.84	0.000
Number of GPs at Nearest Surgery	0.11321	0.001724	65.66	0.000
Percentage of Minority GPs at Nearest Surgery	-0.00478	0.000196	-24.38	0.000
Patient Sex (Female)	0.00919	0.008767	1.05	0.295
<i>Age of Patient</i>				
16 - 24	-0.22569	0.014061	-16.05	0.000
35 - 44	-0.16663	0.011965	-13.93	0.000
45 - 54	-0.35146	0.013871	-25.34	0.000
55 - 64	-0.39594	0.017489	-22.64	0.000
65 - 74	-0.46513	0.021669	-21.47	0.000
75 +	-0.46167	0.023489	-19.65	0.000
(base category for age is 25 – 34 years old)				
<i>Ethnicity of Patient</i>				
African	-0.69489	0.031875	-21.8	0.000
East Asian	0.20510	0.047313	4.34	0.000
Eastern European	0.05819	0.055112	1.06	0.291

European	0.06931	0.024081	2.88	0.004
Hispanic	-0.11843	0.045139	-2.62	0.009
Muslim	-0.41616	0.031656	-13.15	0.000
South Asian	0.13051	0.058795	2.22	0.026
Unclassified	0.00882	0.044964	0.2	0.845
<i>Interaction between Percentage of Minority GPs at Nearest Surgery and Ethnicity of Patient</i>				
African Interaction	0.011145	0.000489	22.78	0.000
East Asian Interaction	-0.00022	0.000776	-0.28	0.777
Eastern European Int.	0.002594	0.000854	3.04	0.002
European Interaction	0.000641	0.000386	1.66	0.097
Hispanic Interaction	0.004685	0.000709	6.61	0.000
Muslim Interaction	0.006092	0.0005	12.18	0.000
South Asian Interaction	0.001658	0.000963	1.72	0.085
Unclassified Interaction	0.002255	0.000708	3.19	0.001
(base category for ethnicity is British)				
Constant	0.721757	0.021294	33.89	0.000
<hr/>				
		Number of obs =	239,525	Log likelihood = -151077.29
		LR chi2(27) =	21101.01	Prob > chi2 = 0.0000

Table 4: Logit regression results testing patient usage of their nearest GP surgery in Southwark.

5. Discussion and Conclusion

This analysis of patient registrations in Southwark demonstrates that different ethnic groups of the population, classified using patient forenames and surnames according to an innovative names classification methodology, exhibit differing patterns of behaviour in accessing GP surgeries. Moreover, there is shown to be an interaction between the ethnicity of the patient, and the likelihood of registration with their nearest GP, contingent on the ethnicity of the GPs in that surgery. While the system of GP registration in Southwark is complex, the research reported here suggests that patients often trade off modest additional travel distances in order to access a local GP surgery. Moreover, the results suggest that the willingness, or the requirement, to make these tradeoffs is more common amongst the African and

Muslim populations and is likely to be connected with the characteristics of the GP surgery, particularly the GPs themselves. However, such trade-offs are highly spatially contingent; all groups have a higher likelihood of using their nearest GP surgery the closer they live to it. This reflects the role of the GP surgery as a place that provides local services in a way that tries to serve the population as a whole (i.e. spatial equity). This analysis benefits from the individual level at which it is conducted, deriving door-to-door network distances and spatial referencing at the household-level. Further work understanding the characteristics of the GP surgeries that might be driving differential registration behaviors could help develop delivery of healthcare in the UK within the local community remit specified by the NHS, consistent with the mantra of improving patient choice.

It is also evident that ethnicity is only one of a number of factors driving patient registration behaviors, albeit an important one in the context of Southwark, and one that predates the most recent proposals on promoting patient choice in NHS primary care. Opening up choice in the ways suggested by UK NHS reforms may weaken the effect of distance on the patterning of registrations with a GP surgery and confer greater importance upon the characteristics of the patients and of the services they seek. In this respect it is important to understand the preconditions of registration as a benchmark to assessing whether reform manages to effectively maintain levels of equity, or whether there is a discernable polarisation of patients and services. This is set to become an issue of increasing importance if NHS reform creates a significantly increased role for GPs in the procurement and delivery of secondary healthcare services. Such insights might also be gained from analyzing reforms to other healthcare systems: by analogy, has the U.S. healthcare reform really made accessing healthcare any fairer on the ground? Similarly, and more broadly, how people use public (and private) services is an important part in understanding the functioning of neighbourhoods and the coherence of communities.

Notes

¹ More information regarding the index of multiple deprivation (IMD) for 2010 can be found here:

<http://www.communities.gov.uk/communities/research/indicesdeprivation/deprivation10/> (last accessed 17 October 2011).

² More information regarding Onomap can be found at: <http://www.onomap.org> (last accessed 17 October 2011).

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Correspondence: Department of Geography, Queen Mary, University of London, Mile End Road, London E1 4NS, UK, email: d.lewis@qmul.ac.uk (Lewis); Department of Geography, University College London, Pearson Building, Gower Street, London WC1E 6BT, UK, email: p.longley@ucl.ac.uk (Longley).